Published by the Centre of Sociological Research, Poland

ISSN: 1795-6889

Human TECHNOLOGY

Volume 20, Number 1, May 2024

Kristiina Korjonen-Kuusipuro
Adam Wojciechowski
Editors in Chief

https://ht.csr-pub.eu/

Human
TECHNOLOGY

Volume 20, Number 1, May 2024

DOI: https://doi.org/10.14254/1795-6889.2024.20-1

Contents

Human
TECHNOLOGY

ISSN: 1795-6889
https://ht.csr-pub.eu/

Submission: https://ht.csr-pub.eu/index.php/ht/about/submissions

Human Technology is an interdisciplinary, scholarly journal publishing innovative, peer-reviewed articles exploring the issues and challenges within human–technology interaction and the human role in all areas of ICT-infused societies.

Human Technology, published by the Centre of Sociological Research, Poland, is distributed without a charge online.

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu Volume 20(2), June 2024, 1-5

From the Editors-in-Chief

TOWARDS AN INCLUSIVE SUFFICIENCY NARRATIVE

Kristiina Korjonen-Kuusipuro
South-Eastern Finland University of Applied Sciences
Finland
ORCID 0000-0002-8528-0237

Teemu Koskimäki
University of Eastern Finland
Finland
ORCID 0000-0003-0768-7266

Adam Wojciechowski
Lodz University of Technology
Poland
ORCID 0000-0003-3786-7225

Aleksi Neuvonen
Demos Helsinki
Finland
ORCID 0000-0002-5781-0878

Abstract: In this Editorial, we tackle perhaps the most urgent issue of our time – the need to orient lives more towards sufficiency. Achieving such a transformation also requires a parallel paradigm shift in science. In this Editorial, we have two guest authors, Teemu Koskimäki and Aleksi Neuvonen, who are members of the SISU Consortium doing research on sufficiency transition in Finland.

Keywords: *sufficiency, inclusive society, green transition, cultural transformation*

DOI: https://doi.org/10.14254/1795-6889.2024.20-1.0

Sufficiency solutions to wicked problems

“Why, sometimes I've believed as many as six impossible things before breakfast,” wrote Lewis Carroll in Alice in Wonderland. Therein may lie the answer to solving the multiple intertwined ecological and societal crises facing us today. Climate change, overconsumption and biodiversity loss already affect lives in various ways and at various stages. These have even been called *wicked problems* (e.g., Peters, 2017), exceedingly complicated to understand and difficult to solve. Some may even think this is impossible. However, recent research has started to increasingly focus on the potential of sufficiency as a cross-cutting solution (Laurent, 2024).

Sufficiency refers to a sense of “enoughness”, both from the perspective of having enough and not too much (Lage, 2022). From an ecological perspective, sufficiency can define a maximum level of consumption that is environmentally sustainable, but it also needs to consider historical and cultural contexts (Sandberg, 2021). It, therefore, implies not only a reassessment of needs but also a normative shift and a cultural transition.

How humans, technology and sufficiency intersect

Human-technology relations can be seen as part of the cultural sufficiency transformation. The transition towards life within planetary boundaries implies a fundamental shift from the current way of living, altering both consumption and production-related policies and practices (Siivonen 2022). From a cultural and societal point of view, a successful green transition requires a concurrent cultural sustainability transformation, where anticipations of the future shift, novel values and worldviews are co-created in a way that are both intellectually and emotionally supportive of new sufficiency policies and practices (Brosch & Steg, 2021; Siivonen, 2022; Koskimäki, 2021; Jungell-Michelsson & Heikkurinen, 2022).

In the pursuit of a sufficiency transformation within socio-ecological systems, several leverage points emerge as crucial for guiding systemic change (Koskimäki, 2021). Aligning societal goals can lead and motivate sufficiency practices and worldviews. Structural goals of the system can be altered by reorganising incentive systems to guide reductions in overconsumption and in excess or wasteful forms of production — both essential for maintaining ecological and social balance. Revising economic parameters, such as subsidies and taxes, can promote resource equity, discourage unsustainable practices and foster the development of new social innovations and sufficiency-facilitating technologies. Information flows are powerful avenues to influence system behaviour, and this can be tapped into with new policies and techniques that improve the awareness of sufficiency solutions and the problems of overconsumption. Altering system feedbacks — both positive (self-reinforcing) and negative (self-controlling) — can ensure responsiveness to human and ecological requirements, avoiding overshoot and countering potential obstacles to change. Broad engagement in transformation processes can facilitate collective sufficiency innovations, such as through new sharing practices.

By embedding technological advancements, new practices and social innovations within this sufficiency transformation framework, the potential for significant shifts in the levels and patterns of consumption and resource use increases, paving the way for a transformative redefinition of progress and success in our societies. Together, these elements could enable societies to more quickly adapt to ecological and social limits and to experiment with alternative economic and social structures that are sustainable, resilient and adaptive to future challenges.

Sufficiency narrative of human-technology relations

To tackle the wicked problems, the sufficiency transition also needs a new narrative (Hoekstra et al, 2024). People – both decision-makers and ordinary citizens – tend to think narratively. Narratives are pathways that help humans make sense of the world, and they are influenced by values and actions. Sometimes people seem stuck with old ways of seeing and thinking, which implies a deep-seated fondness with our current ways of narrating the world. To imagine, create and implement new solutions, more inclusive narratives are needed.

The currently emerging context of forward-looking cultural narratives offers a novel perspective for studying anticipatory attitudes and anticipatory systems guiding present-day behaviours. Anticipatory attitudes refer to the psychological and cultural aspects of how individuals and societies conceptualise and react to the future. In other words, they are practices of 'using-the-future' in the present. Anticipatory systems are culturally constructed narrative structures that guide these assumptions about the future, thus limiting the inherent uncertainty associated with the future into a more manageable, operational form (Miller, 2018). The rise of new future-oriented narratives in politics and economics signifies a shift in the landscape of these systems.

There is, therefore, a need for building a notion on images of the future that affect human behaviour and initiatives through which societies and organisations direct their collective actions. At present, relatively little is known about the changes in anticipatory attitudes and the underlying anticipatory systems.

In this context, technology, as a tool, can be part of the solution or part of the problem – often it is both. On the one hand, technology creates possibilities to implement sufficiency solutions, to reduce consumption or share our resources more wisely. On the other hand, technology demands natural resources and energy, and these mechanisms can be rather invisible. For example, a shift to a technologically advanced digital economy can seem immaterial, because we do not see how much energy our activity in social media demands or the amount of precious earth minerals that are wasted with each new generation of short-lived devices. Thus, it is necessary to deepen our understanding of the role of human agency and user contributions in technological change, as well as future anticipations guiding them, while also emphasising the need for a more comprehensive approach to human-technology interactions (see, for example, Wiggins et al., 2020).

There is no time to waste. Introducing a new narrative – and future anticipations derived from it - may help us to create visions of what a good life could look like, and the leverage points can help us harness all our potential and skills for the betterment of a shared future guided by the concept of sufficiency. The Human Technology Journal has yet to feature many articles on sufficiency or the green transition. We encourage consideration of these interconnected topics in future publications.

About the guest writers

The theme of this editorial has been inspired by the project Sufficiency Solutions for a Resilient, Green, and Just Finland (SISU), on which Teemu Koskimäki, Aleksi Neuvonen and Kristiina Korjonen-Kuusipuro currently work. SISU is funded by the Strategic Research Council of Finland (Grant No. STN/2023/358763), and it seeks to harness the untapped potential of sufficiency solutions. The project aims to develop a new ecological macro-economic model to simulate resilient green transition and sufficiency scenarios, examine the attitudes toward the future of vulnerable groups and identify ways to maintain citizens' trust in societal institutions during a green transition. Furthermore, the project co-creates new anticipatory beliefs to drive sufficiency and engages key societal stakeholders in Finland in a discussion of sufficiency solutions. The project's overall aim is to ensure that the green transition and basic welfare state promises can be realised even in conditions where the economy does not grow. (https://sisu-stn.fi/en/)

REFERENCES

Brosch, T., Steg, L. (2021) Leveraging emotion for sustainable action. *One Earth*. https://doi.org/10.1016/j.oneear.2021.11.006

Hoekstra, R., Kaufmann, R., Jansen, A., Barth, J., Arntzen, J., Aponte, F.R., Behrens, P., Bothe, P., Brosio, M., Chancel, L., Cui, L., Druckman, A., Fearon, S., Gallant, B., Kormann da Silva, N., Liu, K., Mair, S., Scheffer, P., Schrijver, I., Wang, R., Wiebe, K.S., and Zhu, J. (2024). *Tilting the Scale: A Theoretical Framework to re-direct Public Policy away from Economic Growth towards Sustainable and Inclusive Wellbeing*. WISE Horizons Deliverable D1.4 (Full Report).

Jungell-Michelsson, J., Heikkurinen, P. (2022). Sufficiency: A systematic literature review. *Ecological Economics*, 195,107380.

Koskimäki, T. (2021). Places to Intervene in a Socio-Ecological System: A Blueprint for Transformational Change. *Sustainability* 13, 9474. https://doi.org/10.3390/su13169474

Lage, J. (2022). Sufficiency and transformation–A semi-systematic literature review of notions of social change in different concepts of sufficiency. *Frontiers in Sustainability* 3,954660. https://doi.org/10.3389/frsus.2022.954660

Laurent, É. (2024). *ToBe Project Deliverable D1.2: Sufficiency as a confluence for post-growth streams – Report on the integrated analysis of the different schools of thought*. Sciences Po.

Miller, R. (2018). *Transforming the future: anticipation in the 21st century*. Routledge/Unesco.

Peters, B.G. (2017). What is so wicked about wicked problems? A conceptual analysis and a research program. *Policy and Society*, *36*(3), 385–396. https://doi.org/10.1080/14494035.2017.1361633

Sandberg, M. (2021). Sufficiency transitions: A review of consumption changes for environmental sustainability. *Journal of Cleaner Production* 293, 126097.

Siivonen, K. (2022). Tulevaisuusperintö kulttuurisen kestävyysmurroksen välineenä. (Heritage futures as a mean to cultural sustainability transformation.) In Aalto, Hanna-Kaisa & Heikkilä, Katariina & Keski-Pukkila, Pasi & Mäki, Maija & Pöllänen, Markus (ed.), *Tulevaisuudentutkimus tutuksi – Perusteita ja menetelmiä. (Be familiar with futures studies – introduction and methods.)* Tulevaisuuden tutkimuskeskus, Turun yliopisto, 444–458. https://urn.fi/URN:ISBN:978-952-249-563-1

Wiggins, M. W., Auton, J., Bayl-Smith, P., & Carrigan, A. (2020). Optimising the future of technology in organisations: A human factors perspective. *Australian Journal of Management*, *45*(3), 449-467. https://doi.org/10.1177/0312896220918915

Authors' Note

All correspondence should be addressed to
Kristiina Korjonen-Kuusipuro
South-Eastern Finland University of Applied Sciences (Xamk)
Finland
kristiina.korjonen-kuusipuro@xamk.fi
ORCID 0000-0002-8528-0237

Adam Wojciechowski
Lodz University of Technology
Poland
adam.wojciechowski@p.lodz.pl
ORCID 0000-0003-3786-7225

Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology
ISSN: 1795-6889
https://ht.csr-pub.eu
Volume 20(1), May 2024, 6-24

CONCEPTUAL FRAMEWORK FOR ETHICAL ARTIFICIAL INTELLIGENCE DEVELOPMENT IN SOCIAL SERVICES SECTOR

Miroslavas Seniutis
Institute of Sociology and Social Work
Vilnius University
Lithuania
miroslavas.seniutis@fsf.vu.lt
ORCID 0000-0002-8089-3341

Valentas Gružauskas
Institute of Computer Science
Vilnius University
Lithuania
valentas.gruzauskas@mif.vu.lt
ORCID 0000-0002-6997-9275

Angele Lileikiene
Lithuania Business College, Lithuania
angele.lileikiene@ltvk.lt
ORCID 0000-0002-8414-5906

Valentinas Navickas
Lithuania Business College, Lithuania
valentinas.navickas@ltvk.lt
ORCID 0000-0002-7210-4410

Abstract: *This research explores the domain of Artificial Intelligence (AI) for social good, with a particular emphasis on its application in social welfare and service delivery. The study seeks to establish a universal conceptual framework for ethically integrating AI into the social services sector, recognizing the sector's significant yet underexplored potential for AI utilization. The objective is to develop a comprehensive framework applicable to the ethical deployment of AI in social services, using Lithuania as a case study to illustrate its practicality. This involves analysing the political discourse on AI, examining its applications in social welfare, identifying ethical challenges, evaluating the digitalization progress in Lithuania's public services, and formulating guidelines for AI integration at various stages of delivering social services. Our methodology is rooted in document analysis, encompassing a thorough review of both normative and scientific literature pertinent to the ethical application of AI in social welfare. Key findings reveal that AI's anticipated positive impacts on diverse social and economic areas, as highlighted in political declarations, are being partially realized, as corroborated by scientific studies. Although the global application of AI in social welfare is expanding, Lithuania presents a unique case with its strategic planning gaps in this sector. The developed conceptual framework offers vital criteria for the ethical implementation of AI systems designed to be universally applicable to various stages of social services, accommodating different AI applications, client groups, and institutional environments.*

Keywords: *artificial intelligence, social service, ethics, innovations*

DOI: https://doi.org/10.14254/1795-6889.2024.20-1.1

INTRODUCTION

Background and Problem Statement

There is a field of research known as Artificial Intelligence1 (AI) for Social Good2, which focuses on using AI to benefit society as a whole. It often addresses issues that have a broader impact and are not limited to specific individuals or groups. This includes exploring large-scale social and environmental challenges (Akula & Garibay, 2021; Holzmeyer, 2021; Tomašev et al., 2020), such as how to manage natural (United Nations, 2023; Butler, 2017) and war (Cornebise et al., 2018) disasters more effectively, minimize the effects of global warming, and develop alternative energy sources (Chui et al., 2018).

Alongside this stream of research, there are AI studies that concentrate more on the well-being of individuals and communities, particularly those who are vulnerable or marginalized. Research on AI in social welfare is mostly dedicated to exploring possibilities for automation and enhancement of social welfare systems (Oravec, 2019) comprised of diverse services, policies, and programs aimed at ensuring that people's basic needs – such as health, education, housing, employment, and income security – are met.

Another area of research that can be distinguished is focused on the application of AI in providing specific social services in both the private and public sectors. This type of research is concerned with how organizational structures implement specific interventions, programs, practices, and work methods in assisting the functioning and well-being of individuals, families, or communities. It is considered that AI could be applied in assessing eligibility and needs, making enrolment decisions, providing benefits, and monitoring and managing the delivery of benefits to clients of social services (Ohlenburg, 2020). AI is also being used to conduct risk assessments, assist people in crisis, strengthen prevention efforts, identify systemic biases in the delivery of social services, provide social work education, and predict social worker burnout and service outcomes (Reamer, 2023). These benefits aligned with the efforts of steady digital society development in the EU (Kersan-Škabić & Vukašina, 2023).

However, research on the application of AI in the field of social services is not widely developed. In Lithuania, this is, on one hand, related to the lack of a strategically organized plan for financing AI scientific research, and on the other hand, both in Lithuania and worldwide, the development of AI systems in the social welfare does not proceed very rapidly. AI development is privileged in other sectors that bring more financial benefit (Ministry of Economy and Innovations, 2019). In this regard, proofs of positive impact of AI on business development are obtained by Kolková & Ključnikov (2022); Letkovsky et al. (2023); Roshchyk et al. (2022). Therefore, to promote future research on AI development and implementation in the social service sector, critically evaluated and even competing conceptual frameworks are needed, which will help in creating reliable knowledge.

[1] „Artificial Intelligence (AI) refers to systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals. AI-based systems can be purely software-based, acting in the virtual world (e.g., voice assistants, image analysis software, search engines, speech and face recognition systems), or AI can be embedded in hardware devices (e.g., advanced robots, autonomous cars, drones, or Internet of Things applications)" (Ministry of Economy and Innovations, 2019).

[2] The similar term 'AI for Good' refers to a United Nations project. It is the leading action-oriented, global, and inclusive platform on AI. Its goal is to identify practical applications of AI that can advance the United Nations Sustainable Development Goals and scale those solutions for global impact. (United Nations, 2022).

Current Research

Research on the development and application of AI for social welfare purposes has been particularly expanding in recent years. For instance, computer science representatives like Floridi et al. (2021) and Tomašev et al. (2020) discuss fundamental ethical principles and practices in designing ethical AI or applying AI in the realm of social welfare. Application of AI in law enforcement is analysed by Carton et al. (2016), Fang et al. (2016); in transportation by Bojarski et al. (2016); in education by Lakkaraju et al. (2015); in knowledge management by Bencsik (2021) and Bilan et al. (2023); in healthcare by Ross & Swetlitz (2017); Yu et al. (2018) and Strickland (2019). While there are fewer studies focusing on the ethical aspects of AI application in the social service sector or addressing specific social problems. In the field of social sciences, management, and economics, Kim et al. (2022) provide guidelines for creating AI implementation strategies in social innovation projects. Well-known cases involve AI being used for predicting poverty risk (Jean et al., 2016), mandatory education for homeless youth (Yadav et al., 2016), revealing factors contributing to criminal victimization among homeless adults (Shah et al., 2021), automation of decisions made by child welfare specialists (Gillingham, 2021).

In Lithuania, research is conducted on AI application in medical diagnosis (Janušonytė, 2021; Venclovaitė, D., Stramkauskaitė, A., Kuzmienė, 2022); the possible impact of AI on different aspects of human consciousness is discussed from a philosophical perspective (Vidauskytė, 2021); challenges raised by AI are analysed in constitutional law, the influence of AI on human rights in law enforcement activities, etc. (Juškevičiūtė-Vilienė, 2020; Skardžiūtė, 2018; Zakaras, 2022).

Previous research has primarily focused on general ethical aspects of AI rather than the specific ethical challenges that may arise within the processes of social service delivery. This involves the development of tailored AI solutions for socially vulnerable groups, ensuring their unique needs are addressed while safeguarding their interests.

Research Objectives

The main aim of this study to devise a universally applicable conceptual framework for the ethical implementation of artificial intelligence (AI) in social services, grounded in an unstructured review of international scientific and normative literature on AI's application in social welfare and its ethical governance. This framework, while globally relevant, will include the backdrop of the Lithuanian context, offering insights into its practical application in a specific national setting.

In order to achieve this aim, the study addresses the following objectives, which reflect the main structure of this article: a) To analyse the growing expansion of AI as articulated in political declarations and its implications for society; b) To investigate and document a range of AI applications within the context of social welfare; c) To identify and scrutinize ethical concerns associated with AI; d) To evaluate the current status of digitization in the Lithuanian public sector; e) To delineate the requirements and directions for future research in the field of ethical AI-based engineering of social services.

Research Relevance

It is expected that conceptual framework applied in future empirical research will provide key insights and practical benefits for various stakeholders. Policymakers and service organizers will gain guidance on key aspects like human resource investment, essential skills for AI integration, impact measurement, risks management, and implementation of appropriate AI applications. Service providers and practitioners will benefit from guidelines on maintaining unbiased AI assessments, preserving professional autonomy, and maximizing the benefits of AI. Additionally, service clients will be equipped with information and advice on handling potential harm, ensuring transparent decision-making, and protecting their privacy in the context of AI utilization.

METHODOLOGY

This study presents an unstructured internet sources literature review of 14 normative documents on AI implementation, with a particular focus on international ethical regulations regarding AI, and 40 scientific sources on Ethical AI applications for Social Good, with particular attention to the field of social welfare (see references). This review can be typologically aligned with an expository literature review, wherein social researchers engage in scholarly discourse by offering a detailed explanation of the subject matter. They utilize pilot evidence to foster a comprehensive understanding of the topic under examination (Tayo et al., 2023). This research method was chosen because it grants access to existing knowledge, offering solutions or suggestions aligned with the main research aim, and it also guides the research towards achieving its findings (Yekeen, 2006). The main stages of review such as formulation of selection criteria, selection of sources, data extraction and analysis were performed according to guidelines of Kitchenham and Charters (2007).

The selection criteria for normative literature sources were established to identify documents that regulate AI implementation across multiple levels: nationally in Lithuania, internationally within the European Union and the United States, and globally under United Nations guidelines. Additionally, for scientific sources, the focus was on selecting articles that explore AI implementation in areas such as social good initiatives, social welfare, and public The selection criteria for normative literature sources services, with particular attention to the ethical challenges presented in these areas. As for each qualitative study, it was important that selected sources would be representative in relation to the research problem and not to the volume of available literature or the prevalence of certain viewpoints (Židžiūnaitė & Sabaliauskas, 2017).

To search for relevant normative literature, we utilized Google Search Engine. For scientific literature, our approach included accessing databases with open access, such as Google Scholar, Scopus, and Web of Science using different combination of these keywords: AI, Ethics, Regulation, Social Good, Social Welfare, Social and/or Public Service.

Data analysis in our study was performed through qualitative thematic analysis using MAXQDA 2022 software. This approach enabled us to identify and organize key themes that are crucial to achieving the study's objectives systematically and inductively. Data analysis was conducted according to the following procedure: familiarization with research data, data coding, searching for themes, reviewing them, description, and report preparation (Broun & Clarke, 2014). These main themes are integral not only to the study's structure, reflected in its objectives and section titles, but they also form the core categories of our conceptual framework. These themes include: 1) Applications of AI; 2) AI's impact on various social service processes; 3) the process of delivering social services; 4) Ethical issues in AI usage; and 5) Strategies for risk prevention and resolution in the context of AI implementation in social services.

ARTIFICIAL INTELLIGENCE IN SOCIAL WELFARE: A LITERATURE REVIEW

Rising Expansion and Expectations Toward AI for Society in Political Declarations

There is a growing number of political declarations that not only encourage the development of artificial intelligence (AI) globally but also express the expectation that AI will contribute to social good in a broad sense and ensure social welfare specifically.

Documents from the European Commission and various international bodies over the last five years highlight substantial aspirations regarding the advancement of AI. Firstly, there is a strong ambition for the European Union (EU) to become a world leader in both the development and application of AI. It is expected that each member of the EU will contribute towards establishing the EU as a champion of an AI approach that benefits both individuals and society (European Commission, 2018), there is an optimistic view that AI will significantly contribute to creating a more sustainable society and drive economic growth. This includes improving the efficiency of healthcare and agriculture, aiding in the reduction of climate change, enhancing the productivity of manufacturing systems, and strengthening security measures (European Commission, 2020). The goal set for 2030 is for 75% of European companies to integrate cloud computing, big data, and artificial intelligence technologies. The expectation is that the adoption of AI will lead to improvements in job quality, workplace safety, efficiency, and employee well-being (European Commission, 2021a). Thirdly, one of the EU digital policy objectives for the coming decade is the development of Ethical Artificial Intelligence. This aims to foster responsible and reliable AI that benefits humanity and upholds human rights globally (European Commission, 2021c). Similarly, the Global Goals established by the United Nations in 2015 emphasize that AI should play a crucial role in advancing social welfare, protecting human rights, and promoting environmental sustainability, among other objectives (United Nations, 2015).

Thus, the ambition to become a leader in the AI industry, coupled with elevated expectations for AI's positive impact across various social and economic areas of life, and the simultaneous focus on the ethical challenges of AI implementation, may be considered key elements of the EU's political agenda related to AI development.

Exploring the Range of AI Applications in Social Welfare

Scientific studies confirm that expectations towards AI are being, to some extent, realized. Various AI applications have demonstrated success in solving a range of social problems and in delivering diverse social services within specific institutional frameworks, thereby contributing to the enhancement of the social welfare system (Shi et al., 2020).

Illustrative of this are the following applications: a) Natural Language Processing (NLP) – algorithms capable of reading and comprehending human language have been adapted as virtual assistants for social service users, practitioners, or administrators (Chui et al., 2023); b) Computer Vision (CV) – algorithms that process visual information can enhance public safety by detecting instances of violence, locating missing persons (Trilupaitytė, 2022), aiding the visually impaired (Patel & Parmar, 2022), and assisting seniors with dementia (Bucholc et al., 2023; Chignell et al., 2020); c) Robotics – mobile systems capable of autonomous movement and environmental interaction (Burgard, 2023) can significantly aid in the care and support of the elderly (Wellman & Rajan, 2017); d) Machine Learning (ML) – this method uses historical or real-time data to predict future trends (Engin & Treleaven, 2019), assisting in identifying vulnerable tenant issues (Yeung, 2018), modelling migration patterns (Robinson & Dilkina, 2018), supporting the homeless (Abelson et al., 2014), developing victimization models (Shah et al., 2021), and optimizing food distribution and usage (Shi et al., 2020).

The presented classification of various AI applications, or in other words, the breadth of AI industries, is neither definitive nor exhaustive regarding the fields of its application. However, this overview offers essential insights into the already achieved development of AI in the field of social services in different countries around the world.

Identifying Ethical AI issues

However, numerous ethical challenges arise in relation to the implementation of mentioned AI applications in various socio-economic contexts (United Nations, 2021). These potential ethical challenges are well-summarized in the White House's (2022) Blueprint for AI-related legislation and ethical considerations.

The ethical challenges linked to AI application encompass a spectrum of issues. Firstly, there are security risks and effectiveness concerns, where AI applications might endanger users' safety and amplify deception, affecting trust and reliability. Secondly, algorithmic bias presents a problem, as automated algorithms could inadvertently favor certain demographics, leading to inequality based on age, gender, ethnicity, and more. Thirdly, data privacy issues arise from excessive data collection and use without explicit consent or for unspecified purposes. Additionally, the opacity of AI systems makes their results and processes often difficult to comprehend and verify. Lastly, there's the issue of autonomy loss, where reliance on AI leaves no alternative options for people, limiting their freedom of choice.

The ethical guidelines promoted by the (European Commission, 2019) highlight seven key requirements for AI systems to be deemed trustworthy. Additionally, the document “Artificial Intelligence Act” (European Commission, 2021b) presents a more developed and comprehensive treatment of AI requirements. Many of these requirements are in line with the previously presented White House AI regulations, for example: a) Technical robustness and safety, including resilience to attack and security, a fall-back plan and general safety, accuracy, reliability, and reproducibility. b) Diversity, non-discrimination, and fairness, encompassing the avoidance of unfair bias, accessibility and universal design, and stakeholder participation. c) Privacy and data governance, which covers respect for privacy, quality and integrity of data, and access to data. d) Transparency, including traceability, explainability, and communication.

e) Human agency and oversight, ensuring fundamental rights, human agency, and human oversight.

The additional requirements that are less developed in United States regulation include Societal and Environmental Well-being, which mandates that the entire supply chain of AI systems must be environmentally friendly and beneficial to all human beings, including future generations. It involves a critical examination of resource usage and energy consumption, particularly during the AI systems' training phase. Additionally, AI systems must ensure a positive impact on the social relationships, physical, and mental well-being of users. It is also essential to assess their influence on political processes and structures, including political decision-making and electoral contexts.

One more less developed requirement is accountability, which primarily entails the establishment of mechanisms that enable the auditing of AI systems. This means evaluating and assessing the processes and outcomes of AI systems' algorithms. AI systems should be subject to independent and continuous auditing throughout their entire lifecycle to ensure their safety. AI developers must implement risk and impact assessment procedures, and AI users should have the opportunity to report any negative impacts they might encounter.

The competition for leadership in the AI industry inevitably leads to joint efforts to define ethical principles for AI application and to formulate corresponding AI requirements. Both the European Commission and the White House have promoted a human-centric approach to AI, aiming to enhance individual and collective human well-being. This leads to the fostering of elaboration and international consensus on AI ethics.

Status Quo of the Digitization of the Lithuanian Public Sector

The digitalization of public services (health, education, legal services, etc.) in Lithuania is progressing rapidly. According to the Digital Economy and Society Index (DESI) (European Commission, 2022) Lithuania ranks tenth – 83,85 (score 0 to 10) among European Union countries in this regard. The EU average is – 77, 03 (score 0 to 100) (see figure 1).

However, the pace of AI development in the public sector is not particularly rapid, which could be attributed to the others strategic planning priorities and to the relatively modest financial resources dedicated to AI development in Lithuania. From 2015 to 2018, the public sector invested 26.5 million euros in AI development. For comparison, France's AI development plan is valued at 1.5 billion euros, and China's plan is worth 150 billion euros (Ministry of Economy and Innovations, 2019).

There are known cases where AI systems are applied in law enforcement institutions: police, border guard services, prison department, and other state institutions (Zakaras, 2022), as well as in the health sector, for example in diagnosing diseases (Janušonytė, 2021; Venclovaitė, D., Stramkauskaitė, A., Kuzmienė, 2022) and the business sector (European Commission, 2022), but there are no cases of AI application in the social services sector. It seems that AI development in Lithuania is prioritized in the financial sector. Only 4.45 % of all enterprises (excluding the financial sector) have applied artificial intelligence, whereas the European Union average is 7.91 % (see figure 2).

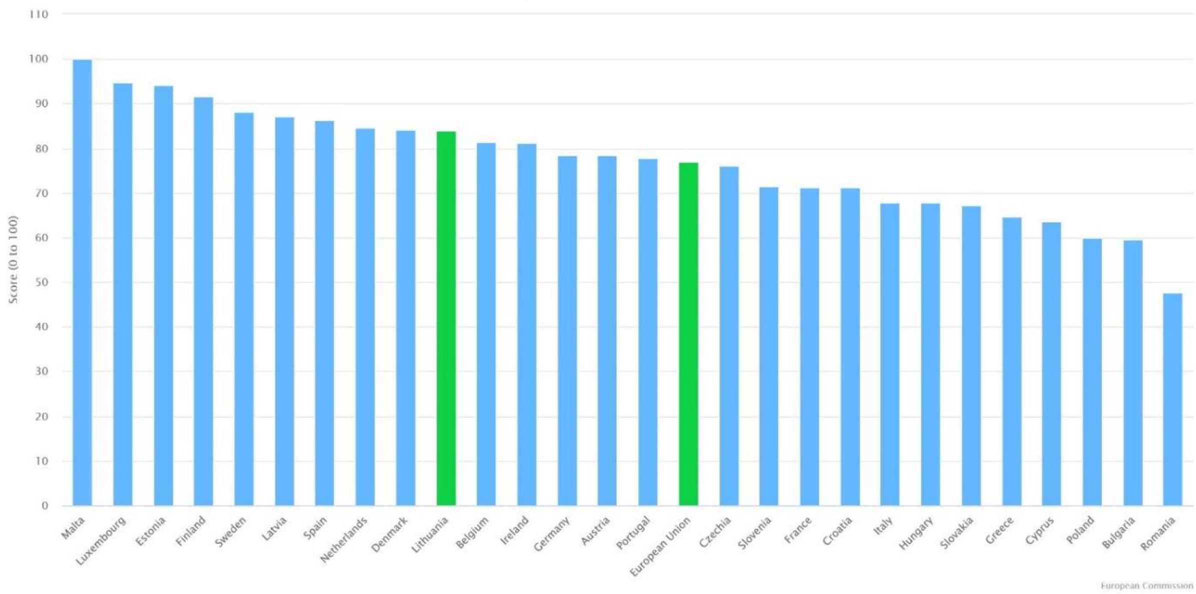

Figure 1. Digital public service for citizens (score 0 to 100), DESI 2022 (data from 2021)

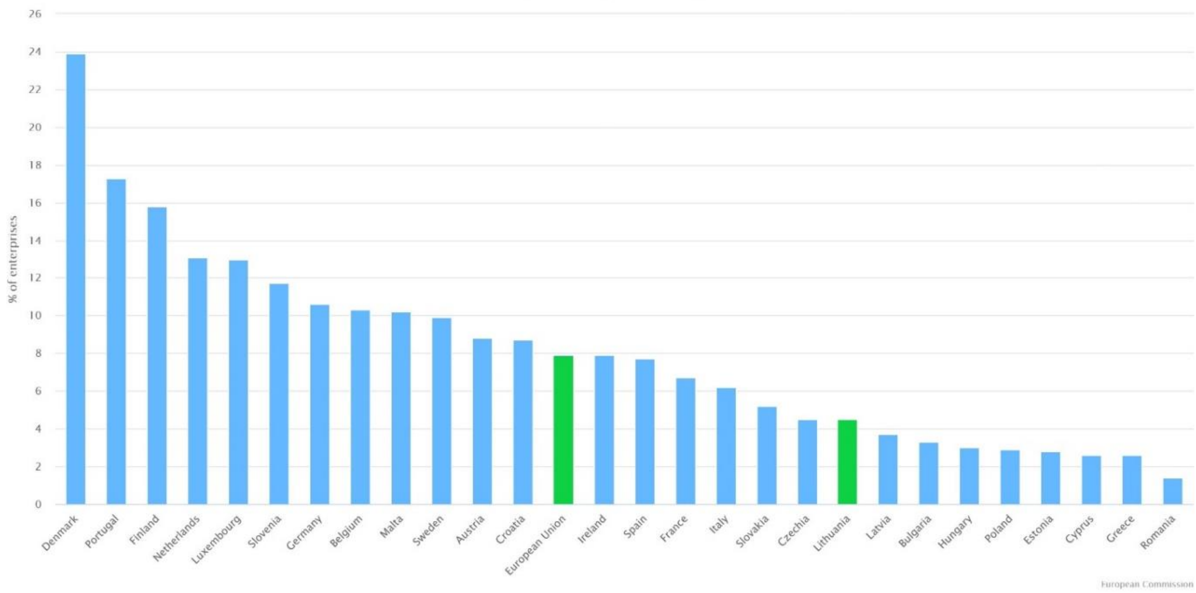

Figure 2. AI implementation across all enterprises (employing 10 or more people and excluding the financial sector) DESI 2022 (data from 2021)

In the Lithuanian Artificial Intelligence Strategy, initiated by the Ministry of Economy and Innovation in 2018-2019, multiple sectors (see figure 3) were pinpointed for prioritized AI development, chosen based on their economic benefit and sectoral impact. The strategy targets a) Manufacturing, aiming to boost productivity through automation; b) Agriculture, employing AI for tasks like robotic harvest collection and intelligent soil analysis; c) Transport, leveraging AI for traffic management and autonomous vehicles; d) Energy, utilizing AI for more efficient energy supply methods, reducing foreign energy dependence; and e) Healthcare, integrating AI to manage increasing patient loads and paperwork, thereby optimizing healthcare delivery.

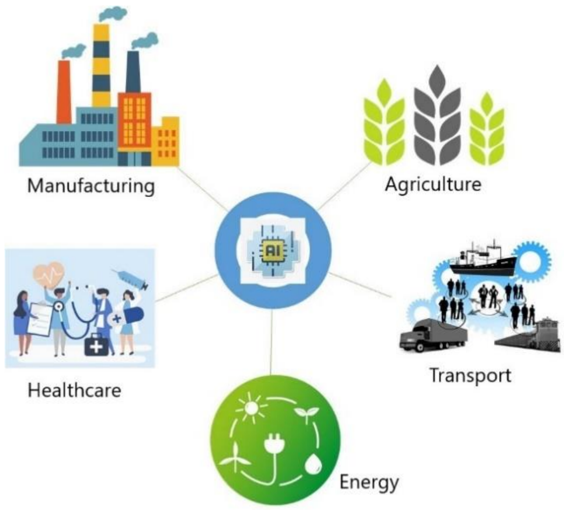

Figure 3. Priority sectors for AI development in Lithuania
Source: own elaboration.

Except the health sector, others are not directly related to social welfare. Therefore, it can be stated that the goals of social welfare are not sufficiently expressed in Lithuania's AI strategy. In a broader sense, the implementation of AI in all these sectors could eventually in long term contribute to a better quality of life of entire population. However, the urgent needs of individuals and groups in need, for whom the social welfare system is designed to provide assistance in various forms, including financial support, healthcare, education, housing, and other services, seem to be insufficiently relevant and prospective to be considered in planning AI development in the country.

In the main strategic documents concerning the state's social welfare, such as the Lithuanian Artificial Intelligence Strategy by the Ministry of Economy and Innovations (2019) and the Strategic Plan by the Ministry of Social Security and Labour (2023), there is a lack of mention of AI implementation in the field of social services. Overall, such plans will have to emerge, along with legal regulation, funding, and specific attempts to create and apply AI in the field of social services. It remains to wish that this process at the political decision-making level would go as smoothly as possible, and at the practical level, opportunities would be created to prepare for the upcoming innovations, such as professional training programs on artificial intelligence, publicly accessible resources about AI opportunities and risks, scientific research, and the like.

RESULTS

Conceptual Framework for Integrating Ethical AI into the Social Service Process

There are well-known national initiatives that involve collaborations between the government, industry (AI companies), researchers (including computer engineers and social scientists), and practitioners (such as social service organizers and providers) (Fox et al., 2022; Bartosz Gajderowicz, 2019). These initiatives are aimed at developing social service solutions based on AI systems. Interdisciplinary and cross-sectoral expert groups are working on social service engineering, which includes how each stage of the social services chain can benefit from engineering design, planning, and delivery. The inclusion of AI systems in this engineering process has the potential to enhance the effectiveness and efficiency of social services. This is achieved by delivering the right services to the right people at the right time, and by preventing and/or addressing potential ethical challenges. For example, a total of $4.9 million in funding was allocated for the implementation of the Compass project in Canada. The goal is to develop a national AI-based platform that aligns the needs of individuals, families, and communities with the right combination of social service options (Darling, 2022).

In this study, a proposed conceptual framework integrates, details, and illustrates potential relationships among four main categories: social service process, the impact of AI on various stages in social service process, AI applications, ethical issues, and risk prevention and solution (see figure 4).

Firstly, the social service process is viewed as a value chain, identifying universal stages such as: design of social services, access to services; identification of client needs; planning assistance; delivery of social services; evaluating service effectiveness (see Saunders, 2016).

Secondly, AI systems can be integrated into various stages of the social service process, potentially having a significant impact on these stages. a) AI can analyse large-scale data to simulate clients' interactions in social services identifying trends and gaps. This helps the design of services focused on real clients' needs and proven practices (Gajderowicz et al., 2014). b) It can provide personalized guidance for users, helping them navigate and access appropriate services more efficiently (Vendeville, 2022). c) AI's data analysis capabilities enhance the precise identification of individual needs by emulating and analysing client behaviour. This understanding of specific client behaviours then guides the customization of suitable assistance methods (Gajderowicz & Fox, 2017). d) AI may enhance the process of searching for and aligning appropriate services with client needs, as well as predicting the potential success rates of these services (Rosu et al., 2017). e) AI can automate routine tasks and decision-making process in service delivery (Jankovic & Bernier, 2023). f) AI can enhance the evaluation process through advanced data analytics, thereby assisting managers and policy makers in improving social services and policies (Vendeville, 2022).

Thirdly, a variety of AI applications, including natural language processing, computer vision, robotics, and machine learning, are examined for their alignment with each stage of the service process (see section 2).

Subsequently, ethical challenges are identified, encompassing issues such as security risks and effectiveness, algorithmic bias, data privacy issues, opacity, autonomy loss, societal and environmental well-being, accountability (see section 3).

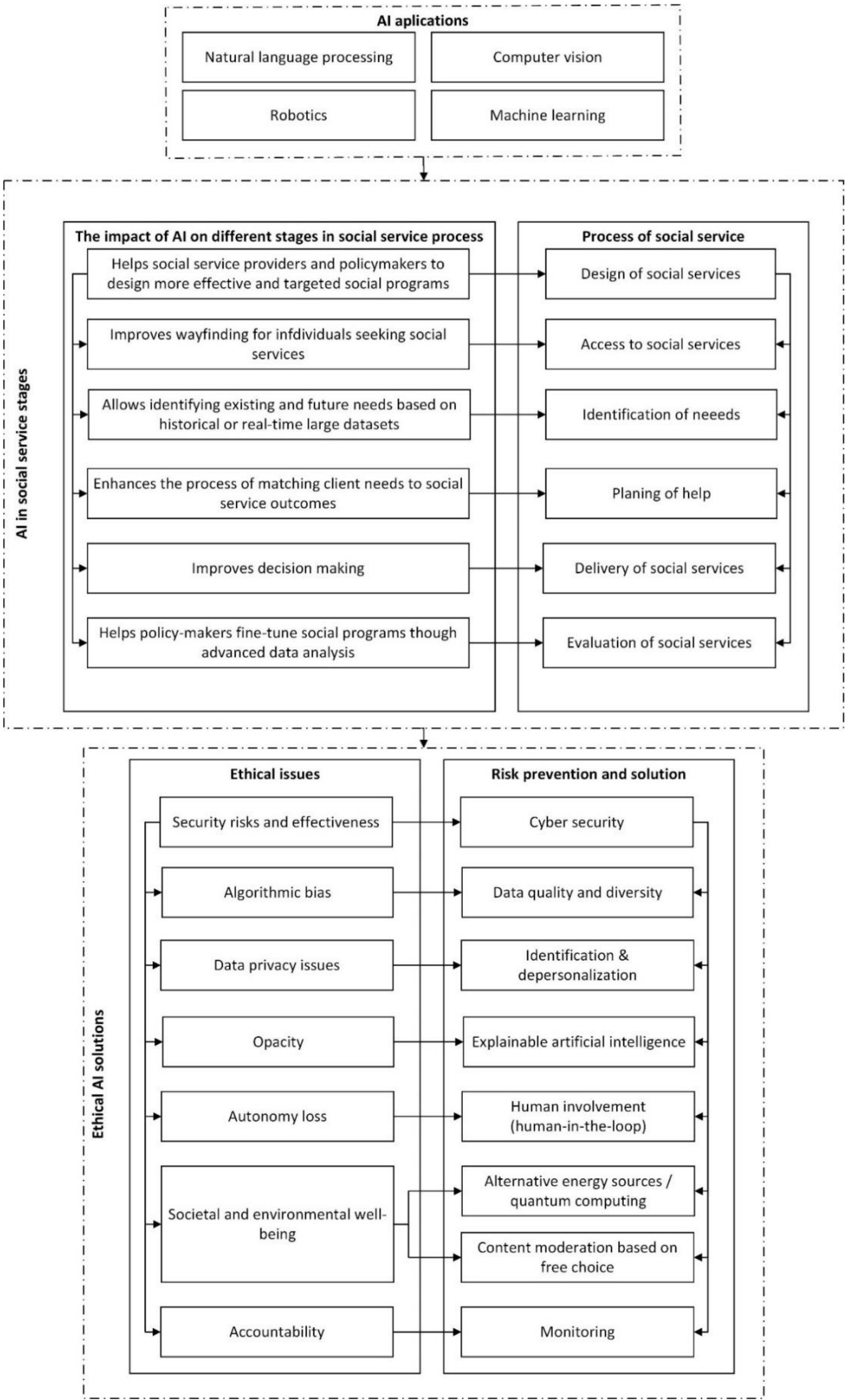

Figure 4. Conceptual Framework for Ethical AI-based social service engineering
Source: own elaboration.

Finally, opportunities for preventing or addressing these challenges are highlighted, including strategies like a) cyber security – the practice of protecting computer systems, networks, and data from digital attacks, theft, or damage. It encompasses technologies, processes, and controls designed to defend against cyber threats (Hendrycks et al., 2022; Zhou et al., 2023); b) data quality and diversity – refers to the accuracy, completeness, reliability, and relevance of data in AI systems. Diversity in data ensures that AI algorithms are trained on a wide range of datasets to avoid bias and to perform effectively across different scenarios (Suresh & Guttag, 2021; Torralba & Efros, 2011); c) identification & depersonalization – identification in AI involves recognizing and distinguishing individual entities, whereas depersonalization is the process of removing personally identifiable information from data sets, ensuring privacy and anonymity (Lison et al., 2021; Patsakis & Lykousas, 2023); d) explainable artificial intelligence (XAI) – the field of AI that focuses on the creation of AI systems whose actions can be easily understood by humans. XAI aims to make AI decisions transparent, understandable, and interpretable (Barredo Arrieta et al., 2020; Molnar, 2019); e) human involvement (human-in-the-loop) – a system design paradigm that incorporates human judgment into AI systems, allowing humans to provide feedback, make decisions, or adjust outputs in real-time, ensuring that the AI remains aligned with human values and goals (Mullainathan & Obermeyer, 2017; Shevlane et al., 2023); f) alternative energy sources / quantum computing – this refers to the exploration and use of renewable energy sources, like solar or wind power, to run AI computations, and the application of quantum computing to dramatically increase computational power for certain types of problems, potentially improving AI efficiency and capabilities (Ajagekar & You, 2019; Jaschke & Montangero, 2023; Li et al., 2022; McDonald et al., 2022); g) content moderation based on free choice – n AI allows users to customize content filters to their ethical preferences and cultural norms, offering a personalized approach to blocking or allowing content instead of a universal moderation policy. This model promotes a balance between preventing harm and upholding diverse expressions (Bubeck et al., 2023; Open AI, 2023); h) monitoring – the continuous observation, checking, and tracking of AI systems' performance and activities. Monitoring aims to ensure that AI systems function as intended, remain secure, and any issues are promptly identified and addressed (Sculley et al., 2015).

This Conceptual Framework presents a general model for evaluating the impact of diverse AI applications across the social service process, pinpointing key ethical concerns that may emerge. It underscores the necessity of incorporating ethical considerations at the initial stages of AI development. While the framework is universally applicable, it is especially pertinent in examining the prospective integration of AI within Lithuania's social service sector. This case study approach offers valuable perspectives on the effective and ethical implementation of AI. The framework's alignment with standard social service stages ensures its adaptability for investigating the potential deployment of various AI systems in delivering a range of social services to different client groups in varied institutional settings.

CONCLUSION

Human-centered ethical AI development, guided by international efforts, is a priority yet remains an unachieved goal. The leadership of the EU and USA in AI regulation and the AI industry raises expectations for AI's positive social and economic impact. Research shows that AI's technological breakthrough has successfully applied many AI systems in the field of social welfare. However, in Lithuania, strategic social welfare documents lack specific AI integration plans, highlighting the need for legal regulation, funding, and AI strategy development in social services. The Conceptual Framework proposed in this research provides critical insights for the ethical and effective integration of AI into social service sectors, exemplified through the Lithuanian context but designed for universal applicability. Moreover, the universality of social service stages enhances the framework's utility in applying it to diverse AI applications across various client groups and institutional settings.

The proposed framework delineates a methodical integration of AI into social service delivery, highlighting the transformative potential of technologies such as natural language processing, computer vision, robotics, and machine learning. These technologies, when judiciously applied, can streamline the processing of information and enhance client interactions through automation, offering personalized and efficient service provision. Delving into the social service stages, the framework elucidates how AI can critically reformulate the lifecycle of services—from the design of predictive and adaptive social programs, to improving accessibility with intelligent guidance systems, from harnessing big data for need identification and planning, to the alignment of services with client requirements through smart matching algorithms. At the ethical forefront, the framework insists on the rectification of algorithmic biases by curating diverse datasets for training AI systems. It underlines the imperative of safeguarding data privacy, asserting transparency in the workings of AI, and upholding accountability for AI-induced decisions, with an insistent recommendation for human oversight in key decision-making junctures. Risk prevention is addressed through a set of practical guidelines that encompass stringent cybersecurity protocols, the enhancement of data quality, the promotion of AI explainability, and the integration of humans in the loop, particularly in sensitive decision-making processes. For pragmatic enactment, the framework advocates regular auditing, stakeholder education, and community engagement, reinforcing the role of AI in social services as a collaborative nexus of technology, ethics, and human welfare.

In the conclusive synthesis of our research, it is imperative to translate the theoretical underpinnings of our framework into actionable recommendations. These practical suggestions are intended to guide key stakeholders—policymakers, service providers, clients, and the community at large—on the responsible integration of AI into the social services sector. For policymakers, the framework recommends the development of robust AI governance models that not only foster innovation but also prioritize ethical considerations. This includes creating policies that encourage the ethical collection and use of data, implementing standards for transparency, and promoting equitable access to AI-enhanced services. Service providers are encouraged to adopt AI solutions that are congruent with the core values of social work, ensuring that such technologies are used to augment, rather than replace, human judgment and empathy. Service providers should also focus on training their staff to work effectively with AI tools and to understand their capabilities and limitations. Clients, as end-users of social services, should be educated on how AI may impact their access to and the quality of services provided. They should be empowered with the knowledge to navigate AI-driven services safely and with awareness of their rights, particularly regarding data privacy. For other involved parties, including technologists, ethicists, and social welfare experts, the framework advises a collaborative approach to ensure that AI technologies are developed and implemented in a socially responsible manner. This includes continuous dialogue on the ethical implications of AI, shared responsibility for risk mitigation, and a commitment to the ongoing evaluation of AI's impact on social welfare.

REFERENCES

Normative documents

European Commission. (2018, April 20). Artificial Intelligence for Europe. https://eur-lex.europa.eu/legal-conhttps://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52018DC0237

European Commission. (2019, April 8). Ethics Guidelines for Trustworthy AI. High-Level Expert Group on Artificial Intelligence. https://ec.europa.eu/futurium/en/ai-alliance-consultation.1.html#:~:text=The AI HLEG presented, and published in April 2019

European Commission. (2020, February 19). White Paper on Artificial Intelligence a European approach to excellence and trust. https://ec.europa.eu/commission/sites/beta-political/files/political-guidelines-next-commission_en.pdf.

European Commission. (2021a, March 9). 2030 Digital Compass: the European way for the Digital Decade. https://eur-lex.europa.eu/legal-content/en/TXT/?uri=CELEX%3A52021DC0118

European Commission. (2021b, April 21). Artificial Intelligence Act. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A52021PC0206

European Commission. (2021c, April 21). Fostering a European approach to Artificial Intelligence. https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=COM%3A2021%3A205%3AFIN

European Commission. (2022). The Digital Economy and Society Index. https://digital-strategy.ec.europa.eu/en/policies/desi

United Nations. (2015). Transforming our world: the 2030 Agenda for Sustainable Development. https://www.refworld.org/docid/57b6e3e44.html

United Nations. (2021). Recommendation on the Ethics of Artificial Intelligence (Issue November). https://doi.org/10.7551/mitpress/14102.003.0010

United Nations. (2022). United Nations Activities on Artificial Intelligence (AI). https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52018DC0237

United Nations. (2023). Building fertile ground for data science in Uganda. United Nations Global Pulse. https://medium.com/un-global-pulse/building-fertile-ground-for-data-science-in-uganda-a950dfd3ca0b

White House. (2022). Blueprint for an AI Bill of Rights. Making automated systems work for the American peopleTEMS WORK FOR THE AMERICAN PEOPLE. https://www.whitehouse.gov/ostp/ai-bill-of-rights

Ministry of Economy and Innovations. (2019). Lithuanian artificial intelligence strategy: a vision for the future.

Ministry of Social Security and Labour. (2023). Strategic Plan.

Scientific sources

Abelson, B., Varshney, K. R., & Sun, J. (2014). Targeting direct cash transfers to the extremely poor. Proceedings of the ACM SIGKDD *International Conference on Knowledge Discovery and Data Mining*, 1563–1572. https://doi.org/10.1145/2623330.2623335

Akula, R., & Garibay, I. (2021). Ethical AI for Social Good. Lecture Notes in Computer Science (*Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics*), 13095 LNCS, 369–380. https://doi.org/10.1007/978-3-030-90963-5_28/COVER

Bucholc, M., James, C., Al Khleifat, A., Badhwar, A., Clarke, N., Dehsarvi, A., Madan, C. R., Marzi, S. J., Shand, C., Schilder, B. M., Tamburin, S., Tantiangco, H. M., Llewellyn, D. J., & Ranson, J. M. (2023). Artificial intelligence for dementia research methods optimization *The Deep Dementia Phenotyping* (DEMON) Network 1 Ilianna Lourida 14. https://doi.org/10.1002/alz.13441

Burgard, W. (2023). Artificial Intelligence: Key Technologies and Opportunities. In K. Frankish & W. M. Ramsey (Eds.), The Cambridge handbook of artificial intelligence (pp. 11–19). Cambridge University Press.

Chignell, M., Matulis, H., & Nejati, B. (2020). Motivating Physical Exercise in the Elderly with Mixed Reality Experiences. In N. Streitz & S. Konomi (Eds.), 8th International Conference Distributed, Ambient and Pervasive Interactions (DAPI) 2020: Vol. 12203 LNCS (pp. 505–519). Springer. https://doi.org/10.1007/978-3-030-50344-4_36/TABLES/3

Chui, M., Harryson, M., Manyika, J., Roberts, R., Chung, R., van Heteren, A., & Nel, P. (2018). Notes from the AI frontier. Applying AI for Social Good.

Chui, M., Issler, M., Roberts, R., & Yee, L. (2023). McKinsey Technology Trends Outlook 2023. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-top-trends-in-tech#tech-trends-2023

Cornebise, J., Worrall, D., Farfour, M., & Marin, M. (2018). Witnessing atrocities: quantifying villages destruction in Darfur with crowdsourcing and transfer learning. AI for Social Good NeurIPS2018 Workshop, NeurIPS ’18,

Darling, E. (2022). Digital Technology Supercluster Announces Investment to Improve the Accessibility of Social Services. https://www.digitalsupercluster.ca/digital-technology-supercluster-announces-investment-to-improve-the-accessibility-of-social-services/

Engin, Z., & Treleaven, P. (2019). Algorithmic Government: Automating Public Services and Supporting Civil Servants in using Data Science Technologies. Advance Access Publication On, 11. https://doi.org/10.1093/comjnl/bxy082

Floridi, L., Cowls, J., King, T. C., & Taddeo, M. (2021). How to Design AI for Social Good: Seven Essential Factors. Philosophical Studies Series, 144, 125–151. https://doi.org/10.1007/978-3-030-81907-1_9/COVER

Fox, M. S., Gajderowicz, B., Rosu, D., Turner, A., & Lyu, D. (2022). An Ontological Approach to Analysing Social Service Provisioning. ISC2 2022 - 8th IEEE International Smart Cities Conference. https://doi.org/10.1109/ISC255366.2022.9922132

Gajderowicz, Bart, & Fox, M. S. (2017). Requirements for Emulating Homeless Client Behaviour. Conference: AAAI Workshop on Operations Research and Artificial Intelligence for Social Good. https://www.researchgate.net/publication/313556478

Gajderowicz, Bart, Fox, M. S., & Grüninger, M. (2014). Requirements for an Ontological Foundation for Modelling Social Service Chains. Proceedings of the 2014 Industrial and Systems Engineering Research Conference Y. Guan and H. Liao, Eds.

Gajderowicz, Bartosz. (2019). Artificial Intelligence Planning Techniques for Emulating Agents with Application in Social Services. University of Toronto (Canada).

Gillingham, P. (2021). Algorithmically Based Decision Support Tools: Skeptical Thinking about the Inclusion of Previous Involvement. *Practice*, 33(1), 37–50. https://doi.org/10.1080/09503153.2020.1749584

Holzmeyer, C. (2021). Beyond ‘AI for Social Good’ (AI4SG): social transformations—not tech-fixes—for health equity. *Interdisciplinary Science Reviews*, 46(1–2), 94–125. https://doi.org/10.1080/03080188.2020.1840221

Janušonytė, E. (2021). Odos vėžio diagnostika ir dirbtinis intelektas. Sveikatos Mokslai, 31(3), 175–180. https://doi.org/10.35988/sm-hs.2021.103

Jean, N., Burke, M., Xie, M., Davis, W. M., Lobell, D. B., & Ermon, S. (2016). Combining satellite imagery and machine learning to predict poverty. *Science*, 353(6301), 790–794. https://doi.org/10.1126/SCIENCE.AAF7894/SUPPL_FILE/JEAN.SM.PDF

Juškevičiūtė-Vilienė, A. (2020). Dirbtinis intelektas ir konstitucinė teisė į teisingumą. *Acta Universitatis Lodziensis. Folia Iuridica*, 93, 117–136.

Kim, E., Jang, G. Y., & Kim, S. H. (2022). How to Apply Artificial Intelligence for Social Innovations. *Applied Artificial Intelligence*, 36(1). https://doi.org/10.1080/08839514.2022.2031819

Oravec, J. A. (2019). Artificial Intelligence, Automation, and Social Welfare: Some Ethical and Historical Perspectives on Technological Overstatement and Hyperbole. *Ethics and Social Welfare*, 13(1), 18–32. https://doi.org/10.1080/17496535.2018.1512142

Patel, K., & Parmar, B. (2022). Assistive device using computer vision and image processing for visually impaired; review and current status. *Disability and Rehabilitation: Assistive Technology*, 17(3), 290–297. https://doi.org/10.1080/17483107.2020.1786731

Reamer, F. G. (2023). Artificial Intelligence in Social Work: Emerging Ethical Issues. *International Journal of Social Work Values and Ethics*, 20(2), 52–71. https://doi.org/10.55521/10-020-205

Robinson, C., & Dilkina, B. (2018). A Machine Learning Approach to Modeling Human Migration. COMPASS ’18: Proceedings of the 1st *ACM SIGCAS Conference on Computing and Sustainable Societies*, 1–9. https://doi.org/10.1145/3209811.3209868

Rosu, D., Aleman, D. M., Beck, J. C., Chignell, M., Consens, M., Fox, M. S., Grüninger, M., Grüninger, G., Liu, C., Ru, Y., & Sanner, S. (2017). A Virtual Marketplace for Goods and Services for People with Social Needs.

Saunders, R. P. (2016). Implementation Monitoring and Process Evaluation.

Shah, O. R., Willoughby, L., & Bowersox, N. (2021). Issues in Information Systems Tackling homelessness through AI powered social innovations: A novel and ground-breaking assessment of criminal victimization of homeless populations in los angeles employing predictive analytics and machine learning models such as ARIMA and LSTM. 22(3), 264–277. https://doi.org/10.48009/3_iis_2021_283-297

Shi, Z. R., Wang, C., & Fang, F. (2020). Artiicial Intelligence for Social Good: A Survey. Preprint: ArXiv:2001.01818. https://aaai.org/Symposia/Spring/sss17symposia.php

Skardžiūtė, J. (2018). Dirbtinio intelekto įtaka konkurencijos teisei: konkurencijos teisės normų aiškinimo ir taikymo problemos [Vilniaus universitetas]. https://epublications.vu.lt/object/elaba:29809699/

Tomašev, N., Cornebise, J., Hutter, F., Mohamed, S., Picciariello, A., Connelly, B., Belgrave, D. C. M., Ezer, D., Haert, F. C. van der, Mugisha, F., Abila, G., Arai, H., Almiraat, H., Proskurnia, J., Snyder, K., Otake-Matsuura, M., Othman, M., Glasmachers, T., Wever, W. de, … Clopath, C. (2020). AI for social good: unlocking the opportunity for positive impact. *Nature Communications* 2020 11:1, 11(1), 1–6. https://doi.org/10.1038/s41467-020-15871-z

Trilupaitytė, S. (2022). Vizualioji kontrolė šiandienos visuomenėse: veidų ir emocijų (ne)atpažinimas. *Politologija*, 2(106), 131–164.

Venclovaitė, D., Stramkauskaitė, A., Kuzmienė, L. (2022). Dirbtinis intelektas oftalmologijoje. *Artificial intelligence in ophthalmology*. https://doi.org/10.37499/LBPG.942

Vendeville, G. (2022). Using AI to optimize social services: Professor Mark Fox among U of T researchers to team up with industry and government. https://www.mie.utoronto.ca/using-ai-to-optimize-social-services-professor-mark-fox-among-u-of-t-researchers-to-team-up-with-industry-and-government/

Vidauskytė, L. (2021). Dirbtinis intelektas: visuomenės infantilizacija ir bejėgiškumas. *Logos* (Vilnius), 109, 71–77. https://doi.org/10.24101/LOGOS.2021.77

Wellman, M. P., & Rajan, U. (2017). Ethical Issues for Autonomous Trading Agents. *Minds and Machines*, 27. https://doi.org/10.1007/s11023-017-9419-4

Yadav, A., Chan, H., Jiang, A., Rice, E., Kamar, E., Grosz, B., & Tambe, M. (2016). POMDPs for assisting homeless shelters – Computational and deployment challenges. *International Conference on Autonomous Agents and Multiagent Systems*, 10003 LNAI, 67–87. https://doi.org/10.1007/978-3-319-46840-2_5/FIGURES/14

Yeung, K. (2018). Algorithmic regulation: A critical interrogation. *Regulation & Governance*, 10, 505–523. https://doi.org/10.1111/rego.12158

Yu, K. H., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. *Nature Biomedical Engineering* 2018 2:10, 2(10), 719–731. https://doi.org/10.1038/s41551-018-0305-z

Zakaras, K. (2022). Dirbtinio intelekto naudojimo teisėsaugos institucijų veikloje iššūkiai žmogaus teisių požiūriu. Mykolo Romerio universitetas.

Secondary sources

Ajagekar, A., & You, F. (2019). Quantum computing for energy systems optimization: Challenges and opportunities. *Energy*, 179, 76–89. https://doi.org/10.1016/j.energy.2019.04.186

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, 58, 82–115. https://doi.org/10.1016/J.INFFUS.2019.12.012

Bencsik, A. (2021). The sixth generation of knowledge management – the headway of artificial intelligence. *Journal of International Studies, 14*(2), 84-101. doi:10.14254/2071-8330.2021/14-2/6

Bilan, Y., Oliinyk, O., Mishchuk, H., & Skare, M. (2023). Impact of information and communications technology on the development and use of knowledge. *Technological Forecasting and Social Change*, *191*, 122519. DOI: 10.1016/j.techfore.2023.122519

Bojarski, M., Testa, D. Del, Dworakowski, D., Firner, B., Flepp, B., Goyal, P., Jackel, L. D., Monfort, M., Muller, U., Zhang, J., Zhang, X., Zhao, J., & Zieba, K. (2016). End to End Learning for Self-Driving Cars.

Bubeck, S., Chandrasekaran, V., Eldan, R., Gehrke, J., Horvitz, E., Kamar, E., Lee, P., Lee, Y. T., Li, Y., Lundberg, S., Nori, H., Palangi, H., Ribeiro, M. T., & Zhang, Y. (2023). Sparks of Artificial General Intelligence: Early experiments with GPT-4. Microsoft Research. https://arxiv.org/abs/2303.12712v5

Carton, S., Helsby, J., Joseph, K., Mahmud, A., Park, Y., Walsh, J., Cody, C., Patterson, C. P. T. E., Haynes, L., & Ghani, R. (2016). Identifying police officers at risk of adverse events. Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 13-17-August-2016, 67–76. https://doi.org/10.1145/2939672.2939698

Fang, F., Nguyen, T. H., Pickles, R., Lam, W. Y., Clements, G. R., An, B., Singh, A., Tambe, M., & Lemieux, A. (2016). Deploying PAWS: Field Optimization of the Protection Assistant for Wildlife Security. Proceedings of the AAAI Conference on Artificial Intelligence, 30(2), 3966–3973. https://doi.org/10.1609/AAAI.V30I2.19070

Hendrycks, D., Google, N. C., Schulman, J., & Steinhardt, J. (2022). Unsolved Problems in ML Safety. Preprint. https://arxiv.org/abs/2109.13916

Jankovic, J., & Bernier, A. (2023). Research shows decision-making AI could be made more accurate when judging humans. https://www.utoronto.ca/news/research-shows-decision-making-ai-could-be-made-more-accurate-when-judging-humans

Jaschke, D., & Montangero, S. (2023). Is quantum computing green? An estimate for an energy-efficiency quantum advantage. *Quantum Sci. Technol*, 8, 25001. https://doi.org/10.1088/2058-9565/acae3e

Kersan-Škabić, I., & Vukašina, M. (2023). Contribution of ESIFs to the digital society development in the EU. *Journal of International Studies, 16*(2), 195-210. doi:10.14254/2071-8330.2023/16-2/13

Kolková, A., & Ključnikov, A. (2022). Demand forecasting: AI-based, statistical and hybrid models vs practice-based models - the case of SMEs and large enterprises. *Economics and Sociology, 15*(4), 39-62. doi:10.14254/2071- 789X.2022/15-4/2

Lakkaraju, H., Aguiar, E., Shan, C., Miller, D., Bhanpuri, N., Ghani, R., & Addison, K. L. (2015). A machine learning framework to identify students at risk of adverse academic outcomes. Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2015-August, 1909–1918. https://doi.org/10.1145/2783258.2788620

Letkovsky, S., Jencova, S., Vasanicova, P., Gavura, S., & Bacik, R. (2023). Predicting bankruptcy using artificial intelligence: The case of the engineering industry. *Economics and Sociology, 16*(4), 178-190. doi:10.14254/2071- 789X.2023/16-4/8

Li, B., Samsi, S., Gadepally, V., & Tiwari, D. (2022). Clover: Toward Sustainable AI with Carbon-Aware Machine Learning Inference Service. Findings of the Association for Computational Linguistics: NAACL , 1962–1970. https://doi.org/10.1145/3581784.3607034

Lison, P., Pilán, I., Sánchez, D., Batet, M., & Øvrelid, L. (2021). Anonymisation Models for Text Data: State of the art, Challenges and Future Directions. ACL-IJCNLP 2021 - 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, Proceedings of the Conference, 4188–4203. https://doi.org/10.18653/V1/2021.ACL-LONG.323

McDonald, J., Li, B., Frey, N., Tiwari, D., Gadepally, V., & Samsi, S. (2022). Great Power, Great Responsibility: Recommendations for Reducing Energy for Training Language Models. Findings of the Association for Computational Linguistics: NAACL 2022 - Findings, 1962–1970. https://doi.org/10.18653/v1/2022.findings-naacl.151

Molnar, C. (2019). Interpretable Machine Learning A Guide for Making Black Box Models Explainable. Leanpub. http://leanpub.com/interpretable-machine-learning

Mullainathan, S., & Obermeyer, Z. (2017). Does Machine Learning Automate Moral Hazard and Error? American Economic Review, 107(5), 476–480. https://doi.org/10.1257/AER.P20171084

Ohlenburg, T. (2020). AI in social protection -exploring opportunities and mitigaiting risks. Deutsche Gesellschaft für Internationale Zusammenarbeit. https://socialprotection.org/discover/publications/ai-social-protection

Open AI. (2023). GPT-4 Technical Report. In Submitted.

Patsakis, C., & Lykousas, N. (2023). Man vs the machine: The Struggle for Effective Text Anonymisation in the Age of Large Language Models. Preprint. https://arxiv.org/abs/2303.12429v1

Roshchyk, I., Oliinyk, O., Mishchuk, H., & Bilan, Y. (2022). IT Products, E-Commerce, and Growth: Analysis of Links in Emerging Market. *Transformations in Business & Economics, 21*(1), 209-227.

Ross, C., & Swetlitz, I. (2017). IBM pitched Watson as a revolution in cancer care. It's nowhere close. moz-extension://b3f4dfef-8263-4daa-9eff-df6d2dfbba2b/enhanced-reader.html?openApp&pdf=https%3A%2F%2Fwww.preventcancer.org%2Fwp-content%2Fuploads%2F2018%2F06%2FIBM_pitched_Watson_as_a_revolution_in_cancer_care.pdf

Sculley, D., Holt, G., Golovin, D., Davydov, E., Phillips, T., Ebner, D., Chaudhary, V., Young, M., Crespo, J.-F., & Dennison, D. (2015). Hidden Technical Debt in Machine Learning Systems. *In Advances in Neural Information Processing Systems* (Vol. 28).

Shevlane, T., Farquhar, S., Garfinkel, B., Phuong, M., Whittlestone, J., Leung, J., Kokotajlo, D., Marchal, N., Anderljung, M., Kolt, N., Ho, L., Siddarth, D., Avin, S., Hawkins, W., Kim, B., Gabriel, I., Bolina, V., Clark, J., Bengio, Y., … Dafoe, A. (2023). Model evaluation for extreme risks. Preprint. https://arxiv.org/abs/2305.15324v2

Strickland, E. (2019). IBM Watson, heal thyself: How IBM overpromised and underdelivered on AI health care. *IEEE Spectrum*, 56(4), 24–31. https://doi.org/10.1109/MSPEC.2019.8678513

Suresh, H., & Guttag, J. (2021, October 5). A Framework for Understanding Sources of Harm throughout the Machine Learning Life Cycle. ACM International Conference Proceeding Series. https://doi.org/10.1145/3465416.3483305

Torralba, A., & Efros, A. (2011, May). Unbiased look at dataset bias. In CVPR 2011 (Pp. 1521-1528). IEEE. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5995347

United Nations. (2015). Transforming our world : the 2030 Agenda for Sustainable Development. https://www.refworld.org/docid/57b6e3e44.html

United Nations. (2021). Recommendation on the Ethics of Artificial Intelligence (Issue November). https://doi.org/10.7551/mitpress/14102.003.0010

United Nations. (2022). United Nations Activities on Artificial Intelligence (AI). https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52018DC0237

United Nations. (2023). Building fertile ground for data science in Uganda. United Nations Global Pulse. https://medium.com/un-global-pulse/building-fertile-ground-for-data-science-in-uganda-a950dfd3ca0b

White House. (2022). Blueprint for an AI Bill of Rights. Making automated systems work for the American peopleTEMS WORK FOR THE AMERICAN PEOPLE. https://www.whitehouse.gov/ostp/ai-bill-of-rights

Zhou, B., Li, B., Qi, P., Liu, B., Di, S., Liu, J., Pei, J., & Yi, J. (2023). Trustworthy AI: From Principles to Practices; Trustworthy AI: From Principles to Practices. *ACM Computing Surveys*, 55(9), 177. https://doi.org/10.1145/3555803

Authors' Note

All correspondence should be addressed to
Miroslavas Seniutis
Institute of Sociology and Social Work, Vilnius University, Lithuania
miroslavas.seniutis@fsf.vu.lt

Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 20(1), May 2024, 25-44

EXPLORING LAW ENFORCEMENT OFFICERS' EXPECTATIONS AND ATTITUDES ABOUT COMMUNICATION ROBOTS IN POLICE WORK

Xiaoti Fan
Department of Communication Arts
The University of Alabama in Huntsville
USA
ORCID 0000-0002-4755-1040

Roya Salehzadeh
Mechanical, Robotics, and Industrial Engineering Department
Lawrence Technological University
USA
ORCID 0000-0002-6522-7615

Soroush Korivand
Bobby B. Lyle School of Engineering
Southern Methodist University
USA
ORCID 0000-0001-7407-8159

Fareed Bordbar
The University of Memphis
USA
ORCID 0000-0002-2212-0025

Christian Cousin
Department of Mechanical Engineering
The University of Alabama
USA
ORCID 0000-0003-1845-9541

Darrin J. Griffin
Department of Communication Studies
The University of Alabama
USA
ORCID 0000-0001-9203-7633

Nader Jalili
Bobby B. Lyle School of Engineering
Southern Methodist University
USA

Abstract: *This study explores the perspectives of law enforcement officers (LEOs) on the implementation of communication robots in police work. Through two approaches - open-ended questionnaires (N = 37) and focus group discussions (N = 14) - the research aims to gather LEOs' opinions and attitudes on the potential future use of these robots. The findings reveal a general skepticism among LEOs, who express low trust in communication robots. Despite this, a majority acknowledge that robots could enhance communication effectiveness in policing. The study highlights the need for increased public education and enhanced performance accuracy of robots to address LEOs' concerns and foster greater acceptance of this technology in law enforcement.*

Keywords: *robot, communication, law enforcement, police.*

DOI: https://doi.org/10.14254/1795-6889.2024.20-1.2

INTRODUCTION

The use of robots in law enforcement has been a long-debated topic among scholars and the public. Some scholars have argued in favor of using robots in law enforcement as robots have proven to be suitable replacements for law enforcement officers (LEOs) in risky situations. Therefore, they hold a great promise to maintain the safety and security of both civilians and LEOs (Murphy, 2004). Alternatively, other researchers have opposed employing robots in law enforcement, arguing that robots used in law enforcement raise ethical and legal questions and concerns. Therefore, the current study aimed to analyze the different perspectives LEOs have on using robots in law enforcement. To obtain these perspectives, the project introduced a novel communication robot design to LEOs and explored their sentiments regarding factors such as communication, trust, and their attitudes towards this type of technology. This endeavor also allowed for the consideration of relevant ethical and legal considerations of the study participants.

Robots have been designed to be used in a variety of situations in the law enforcement context. Most commonly, robots were used for dangerous situations such as hostage, security, and surveillance (Karthikeyan et al., 2015; Matthies et al., 2002; Patel et al., 2013; Zheng, 2019). Additionally, they were designed for bomb searching and disposal (Day et al., 2008; Motaleb et al., 2016; Zeng et al., 2007). During mundane tasks, robots can be implemented in traffic control in replacement of human traffic police (Gong et al., 2017). They can also be used for object recognition, searching, and detection (Flann et al., 2002). Moreover, robots could be of great assistance in unexpected circumstances, such as serving as a medic during the COVID-19 pandemic (Javaid et al., 2020; Sahu et al., 2022), as well as in disaster rescues (Nath, Arun, & Niyogi, 2019). This study explores additional scenarios in which communication robots can be implemented.

However, to accomplish a task by a human-robot team, humans must trust in the robot teammate and believe that the robot will protect the interests and well-being of each individual on the team (Hancock et al., 2011). The human trust level in the robot partner will be critical in high-risk situations, such as combat missions (Chen et al., 2008; Chanel et al., 2020), or when a human’s life is at risk - such as a suicidal situation (Rastogi et al., 2018). Trust is of pivotal importance in human-robot interaction (HRI) as it significantly affects the willingness of people to accept robot-produced information or follow a robot’s suggestions and ultimately benefit from the advantages of the robot’s presence in the system (Freedy et al., 2007). Trust also influences the decisions humans make in uncertain environments where they partner with robots (Park et al., 2008). Accordingly, as law enforcement consists of numerous high-risk decision-making situations, trust is one of the cornerstones of the HRI in this profession. The level of trust in robots in HRI varies in the range of very low to very high, which both may have an adversary effect. In the case of excessive high trust, overreliance on and misuse of the system occurs, or in the case of low trust, disuse of the entire system may happen (Lee & See, 2004; Parasuraman & Manzey, 2010; Parasuraman & Riley, 1997). As a result, distrust and overreliance can deteriorate the efficiency of the HRI.

Nonetheless, recent studies have demonstrated that LEOs generally have a high level of trust after obtaining training using law enforcement communication robot platforms (Bordbar, Salehzadeh, Cousin, Griffin, & Jalili, 2021). Training with communication robots led to a reduction of LEOs’ initial negative attitude toward the robot. It resulted in high general levels of trust in their interactions with communication robots when LEOs completed the training (Bordbar et al., 2021). Therefore, in the current study, LEOs' trust levels were investigated further to explore the conditions that may result in excessively high or low levels of trust, i.e., what factors lead to high or low levels of trust towards a communication robot. The goal of exploring these factors is to enable future researchers or police training to adjust to these factors so that higher trust levels can be appropriately obtained from LEO communication robot operators.

Trust in robots, robot acceptance, and attitudes towards robots are also influenced by other factors, including human-related and robot-related factors. Human-related factors are associated with either human abilities or human characteristics. Human abilities include attention capacity/engagement, expertise (Navarro et al., 2021), competency, operator workload, previous experience, and situation awareness. Human characteristics refer to demographics, personality traits, attitudes toward robots, comfort with robots, self-confidence, and propensity to trust (Hancock et al., 2011). Additionally, culture is a significant human-related factor that impacts robot acceptance. Several studies in the past have shown that cultural differences affect one's attitude toward robots (Bartneck et al., 2005; Bartneck et al., 2005; Huerta et al., 2012). This is primarily due to different extents of exposure to robots through media or personal experiences among cultures. Demographic differences such as age and gender impact trust and acceptance in robots (Hoff & Bashir, 2015). Self-efficacy perceptions or self-beliefs is another human-related factor that affects the acceptance of new technologies.

The concept of self-efficacy in robot acceptance has been studied in the field of both social robots (e.g., humanoid, pet, service robots) (Latikka, Turja, & Oksanen, 2019) and non-social robots (e.g., collaborative robots) (Bröhl et al., 2019). Overall, due to the significance of all the above-mentioned human factors in robot acceptance and trust, robots could be considered a help or hindrance in society. In the context of law enforcement, the general attitude toward robots could be both positive and negative (Yunus & Doore, 2021; Szocik & Abylkasymova, 2021). Robots have gained increased traction to be used as a tool to augment and replace required functions by LEOs. Robots could benefit LEOs in some situations, such as explosive ordinance disposal or surveillance, since using robots provides safer alternatives to direct human activities (Murphy, 2004; Theodoridis & Hu, 2012). However, many scholars have raised concerns about the consequences, particularly if robots are allowed to use force, make decisions, and act autonomously (Asaro, 2016; Howard & Borenstein, 2018). Furthermore, the lack of transparency and accountability in robotics has been discussed (Royakkers & van Est, 2015). Moreover, many LEOs are still reluctant to adopt robotics into their day-to-day operations because of the robots' complexity, cost, the burden of use, and other limiting factors. It is safe to conclude that robots could have a significant impact on law enforcement in the future. Nevertheless, using robots as a tool in law enforcement will face major challenges due to the complexity of the social and physical space in the public domain (Salvini et al., 2010).

However, for the robot that is supposed to be used as a communication medium, the communication function of a robot is also crucial when operating in the field. Robots' communication abilities should be developed to build relationships empathy, and trust in human-robot interaction. Miscommunication or ineffective communication could lead to severe consequences. Back in the 1990s, robots were starting to develop communication abilities that involved following and responding to simple, pre-programmed commands. However, they were not able to process and initiate emotional speeches and were not able to communicate nonverbally (Mavridis, 2015). As such, natural language and speech planning in robots-human communication are needed, especially when communicating with non-experts (Mavridis, 2015) such as civilians. Past research has tried to enhance robot communication abilities as well as prevent communication interference. For instance, Brooks et al. (2012) employed a natural and continuous language system during communication between robots and operators to acquire accurate commands during tasks. Furthermore, technologies were developed to prevent hacking and enhance hacking detection in robot communications (Abeykoon & Feng, 2017). Efforts were also made to enhance communication abilities and communication links between robots and the operators when the link becomes low such as inside a building (Nguyen, Farrington, & Pezeshkian, 2004). In addition, abilities to pick up non-verbal cues and respond to natural nonverbal behaviors were researched (Vogeley & Bente, 2010). In the revolutionary world, social robots have emerged as a unique category. These robots are specifically designed with social-communicative functions to interact with humans as communicative entities (Gasser, 2021).

With taking all above mentioned into account, this study uses a conductive method, hoping to get a clear and comprehensive understanding of LEOs' opinions towards using robots in law enforcement. The selected work domain was law enforcement, and our selected workers were LEOs. The selected workplace was the daily face-to-face interactions between LEOs and civilians. Directed by past research and the existing gaps, there are three main aims of this study: 1) to understand police officer's attitudes towards communication robots, 2) to introduce critical factors affecting the acceptance of the communication robot in the law enforcement context, 3) to discover the barriers for further development of communication robot in law enforcement.

METHOD

Study Design

This study is a part of a larger mixed-method study that involved survey collections. The two parts discussed in this study include open-ended responses from LEOs' training sessions and two focus group sessions. The training sessions took place in several locations that involved LEOs participating in eight-hour training sessions consisting of topics in communication (i.e., nonverbal, intercultural, mediated) and robotics (i.e., robots' application, robots' functionalities, robotic technologies). In Study 1, participants underwent training sessions focused on communication and robotics. During these sessions, they had the opportunity to operate prototype communication robots. The prototype features a wheeled robot that can be controlled via game controllers, equipped with a manipulator, a microphone, a stereo camera, a 3D camera, a touchscreen display, and a Pan servo (See Figure 1). As LEOs operate the robot, they can simultaneously see, hear, and communicate with the recipient. Additionally, the robot is equipped with a mapping function that can provide a map of the target building before LEOs enter it. The overarching goal of this larger project is to assess whether these trainings and robot operations influence LEOs' attitudes and acceptance of robot usage in law enforcement, as well as to gather feedback that could inform the improvement of robot design. For the purposes of this paper, the data analyzed are from the pretest responses, collected before LEOs had any experience with the communication robot. Their only exposure to the robot was its presence on display, allowing them to observe it and form preliminary impressions of its capabilities. The focus groups in Study 2 were conducted via Zoom with LEOs with various levels of experience to gather their responses and opinions regarding employing robots in law enforcement. These participants did not receive any trainings nor interacted with the robot prototypes.

Figure 1. Communication Robot Prototype

Study 1 (Curriculum/Training)

Participants

A total number of N = 54 sworn LEOs with different years of field experience participated in the communication training sessions and training with the robot prototype. The responses from N = 37 officers who have completed all the surveys were considered in this study. The LEOs of various ranks (e.g., police officer, deputy sheriff, investigator, chief, captain) were recruited from four law enforcement agencies in the State of Alabama. Most participants were male (89.2% male, 8.1% and 2.7% not reported) and the average age of the participants was 40.2 years (n = 37, M = 40.2, SD = 13.38). The average years of experience of the participants were 17.03 (n = 37, M= 17.03, SD= 11.04). The education level of the participants was recorded as high school degree or equivalent (5.6%), some college/no degree

(36.1 %), associate degree (13.9%), bachelor’s degree (30.6%), master’s degree (11.1%), and doctorate or professional degree (2.8%).

Procedure

For the recruitment process, an email attached with a copy of the informed consent form (for participants' prior review), was sent to senior officers, police executives, supervisors, and/or appropriate personnel at the City of Tuscaloosa Police Department (TPD), the Center for Best Practices in Law Enforcement at Jacksonville State University (JSU), and the Alabama Peace Officer’s Standards and Training Commission (APOSTC) Law Enforcement Academy – Tuscaloosa (LEAT) who work with police officers in training, or requiring continuing education hours. In that email, the scope of research and the project aim was explained. It was mentioned that researchers at The University of Alabama were investigating the effects of robots on the future of law enforcement. The project aims described as developing a highly interactive, remotely operated robotic platform to equip law enforcement officers with the ability to remotely communicate and interact with various individuals for purposes including collaboration or assistance. Also, it was mentioned that officers would operate robot prototypes and provide feedback.

Participants in the study were involved on-site at either the City of Tuscaloosa Police Department (TPD), the Center for Best Practices in Law Enforcement at Jacksonville State University (JSU), or the Alabama Peace Officer’s Standards and Training Commission (APOSTC) Law Enforcement Academy –Tuscaloosa (LEAT). Four sessions were conducted in total, two sessions at the Center for Best Practices in Law Enforcement at Jacksonville State University (JSU), and one in each of the other departments. No compensation was provided to individuals for participating in this research study. There were no direct benefits to participants aside from obtaining hands-on experience piloting a social robot and learning about the topics of nonverbal and intercultural communication. The topics were specifically selected in agreement with the agencies’ administrators and counted towards officers' required continuing education hours.

The study consisted of an 8-hour (8:00 am –5:00 pm) day of training and testing. These days were divided into two sessions: 1) Communication training and 2) robot testing and piloting. In the communication sessions, officers were provided with training on topics related to nonverbal communication (e.g., facial expressions & emotion, paralanguage & deception) and intercultural communication (defining culture, dimensions of culture, research on differences across cultures & police), computer-mediated communication (CMC), effective communication, and robotic-mediated communication & police work intended to improve awareness and skills of officers on these topics. Officers also participated in a cross-group threats exercise. In the robotics session, first, our research group provided training on topics related to robot design, robot interface, robot communication channels, and robot behaviors. Also, there was a discussion on the future of robots in police work and how robots are expected to be used as a tool in the future to help officers. In the end, officers worked alongside robotics trainers to pilot, control, and navigate a robot through a simulated scenario(s) and provided us with their feedback. The entire day of training and testing was designed to satisfy the required continuing education hours. During both sessions, officers actively participated in discussions, received training, and filled out surveys.

Table 1. Study 1 Coded Themes

Themes	Category	Codes
Scenarios	• Human-created situation • Non-human created situation	• Bomb • Hostage • Search and detection (e.g., collect information, map, search, detect danger, detect criminals) • Tactical • Mediation • Officer safety & protection • SWAT • Active shooting • Public safety (e.g., save life, buy time) • Delivery/removal/moving • Neutralizing capability • Routine activities (e.g., parking tickets, tag/license scan, traffic control, identification) • live medical assistance • Force multiplier • In stressful/threat situations • Negotiation (other than hostage) • First response (fire/rescue/ emergency medical technicians) • Natural disasters • Hazardous scenes
Trust	• Low trust • High trust	• Failure during operation • Human-robot communication is not as effective as human-human communication (loss of interpersonal contact, attention, touch) • Financial risk if the robot fails • Fear of robots/anxiety • A robot is less threatening than a police officer • No risk in using robots • The safest way to use a robot
Attitude	• Positive (help) • Negative (hindrance) • Both (what is needed/challenges)	• Force multiplier • Alleviate the possibility of perceived immediate danger • Greater capabilities and features than the human (can be our eyes and ears when needed, no emotions, no bias) • More advanced and accepted in future • Reliance of LEOs on the assistance of robots (over dependency on robots) • Inability to have human senses • Robots are not practical in every situation/risky to use robot • Training in robotics might be expensive • Ethics • Emotional adverse effect, rapport • Education/training • Situation dependent • Budget needed/funding • More robot/increasing the number • Willingness/ familiarity/ feeling comfortable • Administration/permission/ regulation
Communication	• Better communication • Worse communication	• Safer communication (direct communication is not safe) • Open/effective communication • Communication with suspects, victims, and disabled people • Effective communication with disabled people • Translation & interpretation (communicate in various languages) • The communication is difficult by robot

Study 2 (Focus Group)

Participants

The focus-group study was performed in two sessions. In the first session, six male police officers ($N = 6$) participated, whose expertise was in different policing areas, including safety, emergency management, teaching criminal justice investigations in domestic terrorism and violent crimes, and law enforcement academy. These participants were recruited from Jacksonville State University, Jacksonville Police Department, APOSTC Law Enforcement Academy in Tuscaloosa, and Flathead Valley Community College. The positions of these participants were director ($n = 4$), officer ($n = 1$), chief ($n = 1$). The participants had a range of job experience from 16-37 years ($n = 5$, $M = 27.4$, $SD = 7.55$).

In the second session of the focus group, eight male police officers ($N = 8$) participated who have worked in different scopes of law enforcement, including patrol, homicide unit, threat assessment, law enforcement academy, bomb tech, crime center, narcotic, robot, and drone units. These participants were recruited from Tuscaloosa Police Department, Oxford Police Department, and Jacksonville State University. The rank of these LEOs were sergeant ($n = 5$), investigator ($n = 2$), lieutenant ($n = 1$). The range of job experience of the participants was from 4.5-23 years ($n = 7$, $M = 16.29$, $SD = 5.54$).

Procedure

Two focus groups were conducted with two law enforcement populations. Due to COVID-19 restrictions, both focus groups were conducted online via the Zoom platform. The time duration of both meetings was 90 minutes.

A criminal justice professor who specialized in international crime prevention acted as the moderator for both focus group sessions. Using the experience and connection of the criminal justice professor, the research team utilized a convenience sampling method and, consequently snowball sampling techniques to recruit participants for both focus groups. LEOs’ consent was obtained online via the DocuSign application before the focus group meetings. Other research team members who participated in the zoom call were a communication professor specializing in nonverbal communication and a mechanical engineering professor specializing in robotics. These two professors assisted the moderator with questions from their respective disciplines. The zoom call was designed to be confidential, and only the audio recording in progress was preserved.

The outline of both focus groups was as the following: the first 10-15 minutes were spent explaining to the participants and reviewing the confidentiality and audio-only features of the sessions. Participants' names were removed from the screen labels and instead were replaced with their ranks when speaking to maintain their anonymity. Next, the moderator explained the project and the conceptualization of communication robots to the participants.

Data Analysis

In both studies, thematic analysis was employed as the primary analysis method (Bulmer, 1979). Thematic analysis is a flexible and accessible technique that is well-suited for identifying, analyzing, and reporting patterns within data. It can be adapted to various research questions, data types, and theoretical frameworks, making it particularly suitable for our interdisciplinary research team (Braun & Clarke, 2006). The method's ease of application allows researchers with varying levels of experience to explore the depth and complexity of their data, providing rich insights into participants' experiences and the social context. Thematic analysis also facilitates the comparison of themes across different data sets, which is valuable in studies involving multiple groups or sites (Guest, MacQueen, & Namey, 2012). Moreover, its systematic and transparent approach enhances the credibility and trustworthiness of the research findings (Nowell, Norris, White, & Moules, 2017).

The pretest qualitative dataset obtained from pretest-posttest surveys was used to generate the list of codes. The code generation was done in a team-based approach. Group meetings were held to generate general themes. Then, team members individually worked on the data and generated their codes. At the next step, several meetings were conducted to discuss the codes, and finally, based on all team members' agreement, the codes were combined, and the code book was finalized.

Transcripts from the two focus groups were redacted and cleaned up by two team members. A draft code book was then developed among the first four authors that contained main themes and categories. Then, each author individually coded one of the transcripts and met with another team member to discuss the codes and reach agreements on the codes. Next, all four authors met and discussed both transcripts and cross-examined the codes. Codes were combined and finalized after group discussion and cross-examination.

Table 2. Study 2 Coded Themes

Themes	Category	Code

Situations/scenarios to use robots	• Serious/dangerous situation
	• Non-serious/non-life threating situation
	• De-escalate situations & prevention
		• Bomb squad
		• hostage situation/mental illness/barricaded man
		• Active shooting
		• Surveillance/security Check
		• Detention/jails
		• Parking areas
		  • De-escalate
		  • Prevent dangerous/ safety

Trust in robots	• High • Low • Depending	• Already in use • Lose robot/money but save people • Skeptical • Taking away the rapport • Situation dependent
Acceptance/attitudes towards robots	• Positive • Negative • Depending (challenges for implementation)	• Capabilities beyond human abilities • Build rapport • More presence-exposure-acceptance • Preference for human/against robot • Intimidating • Lack of budget • Affordable cost • Training of officers • Robot accuracy • Education of the public • Community outreach and influencers
Communication	• Better communication	• Providing more communication abilities/ communicate more effectively • Report/provide more information • Negotiation

RESULTS

Scenarios Study 1

When asked about what situations robots can be used in law enforcement, LEOs identified a variety of human-created or human-related situations and/or scenarios. Among the several highly mentioned scenarios, the search and detection task were the most frequently reported theme, which includes information collection, mapping, searching, detecting dangers, detecting criminals, navigating, and surveillance—followed by first response scenarios that include fire, rescue, and emergency medical technicians (EMT). Additionally, the responses indicated robots could be used for keeping officers safe and providing protection, as well as prompt public safety that it could save lives and buy more time in such dangerous situations. Although many LEOs reported robots could be used in generally stressful or threatening situations, two specific dangerous scenarios were highly mentioned in the responses: bomb and hostage. In addition, SWAT and active shooting were also salient themes in the responses. Besides the dangerous situations, non-threatening routine activities were also one of the major themes that emerged from the responses. In specific, LEOs reported robots could be used for giving parking tickets, doing tag or license scans, assisting neighborhood patrol and traffic control, and identifying people. Similarly, robots can be used for any delivery or object removal tasks, as well as EOD tasks. Overall, robots can act as force multipliers to LEOs as they are learning and busy with multiple tasks. LEOs further identified non-human created or accidental situations such as natural disasters and hazardous scenes.

Scenarios Study 2

In the focus group, LEOs discussed various scenarios robots could be used in law enforcement. Many of them mentioned hazardous situations such as hostage situations, mental illness-related situations, and barricaded man situations. Others discussed the use of bomb squads and active shooting scenarios.

Other than serious situations, LEOs also emphasized the use of non-serious or life-threatening mundane scenarios. For instance, robots can be used for surveillance and security check. Moreover, LEOs specifically mentioned the use of robots in detentions and jails. For instance, providing medications to inmates. Lastly, some LEOs discussed the use of robots in parking areas as they can assist in parking and parking tickets.

The last theme that emerged from the focus group study was the use of robots for de-escalation and crime prevention. LEOs believed robots can assist in detecting dangers before anything bad happens so that they can provide prevention abilities.

Trust Study 1

The effect of trust in the functionality of the robot was investigated at two levels of high trust and low trust, based on the LEOs' responses to the questions of this survey. In this regard, the most critical keyword and basically the main concern of the LEOs in the investigation of trust was the failure of the robot during operation. Most of the LEOs showed their skepticism in trusting robots by accentuating the point that the robot may fail during the operation. It was mentioned that this failure could happen due to the susceptibility of the robot, inability to view a scene thoroughly, and malfunction of the wireless transmission and sensors. Additionally, one LEO raised a concern about the potential danger of the robots that they can be hacked and used against LEOs. In addition to this concern, a few officers noted possible financial risk if the robot fails and the fear and anxiety that the robot can cause are the reasons not to trust the robots during the operation.

However, LEOs' trust in the robot during the operation was also expressed. These LEOs' were of the belief that using the robots cannot pose a potential danger, the robot is less threatening than police officers, and there is no risk in using the robot; hence they trust the robot in law enforcement.

Trust Study 2

In the focus group study, LEOs were asked to share their opinion about trust in using robots for communication purposes in law enforcement and what would be the public's reaction if LEOs use the robot more communicatively. Thus, besides the low and high levels of trust, situation-dependent trust is also examined based on the LEOs' responses. LEOs expressed their high level of trust by emphasizing that losing the robot will cause financial loss, but it can save people. Also, LEOs who have worked with robots in law enforcement or have known robots are already in use for policing tasks demonstrated a high level of trust in the communication robot.

On the opposite side, which includes the majority of LEOs' opinions regarding trust, LEOs believed that using robots takes the rapport away from human interactions. Also, LEOs were skeptical of the function of robots in law enforcement, and in this way, they expressed their low level of trust in the robots in law enforcement.

On the contrary, some of the LEOs mentioned that trust in robots depends on the situation. In some situations, the robot can be available to provide more information. In others, the robot may degrade the rapport and create distrust and hence make the situation worse.

Attitude Study 1

In study 1, to assess LEOs' attitudes toward robots, they were asked the following questions: Do you think that robots would be more of a help or hindrance in police work? Why? LEOS had different responses to these questions. The responses have been divided into three categories, positive (i.e., help), negative (hindrance), and both.

LEOs mentioned four kinds of referrals. First, LEOs emphasized that robots have greater capabilities and features than humans. In other words, according to the LEOs, robots can be our eyes and ears when needed, with no emotions, and no bias. Since robots are not emotional, they can mitigate the chances of human emotions getting out of control. Also, robots do not need breaks, they don't get tired, and their situational awareness isn't compromised by the emotions that an officer might be carrying around. Second, LEOs mentioned that robots alleviate the possibility of perceived immediate danger by officers. Robots can limit risks to human officers; they can go where it is not safe for officers; and in some situations, they could take the danger element down when there is a high risk of death for human. Third, LEOs believed that robots could be a force multiplier in law enforcement in a way that robots could supply options and could even de-escalate a situation. Robots could handle the report and recording of the incident much more accurately, they can be placed in uncertain positions (s) to notify or bring awareness, and they could rapidly process routine tasks. In general, robots can help with different aspects of the job. Fourth, LEOs explained that because of the recent advancements in various technologies such as robotics and artificial intelligence, people would be more adoptive respect to those technologies in the future, so this will make robots to be more accepted in the future by LEOs and by society.

Among LEOs that believed robots would be more of a hindrance in law enforcement and the majority of them have mentioned the emotional adverse effect as their reason. LEOs believed that using robots would result in losing interpersonal one-on-one connections and interactions. Human-human communication is more efficient, and some people feel more comfortable communicating with a human rather than a robot. It has been mentioned by several of the LEOs that robots might not be practical in every situation, and this is a hindering factor in using robots. In addition, it was believed among several LEOs that training on robots is an expensive process that could create a barrier to adopting robots by law enforcement.

The majority of LEOs discussed that robots in law enforcement could be both of help and a hindrance, and it completely depends on the situation the robot is used. LEOs considered robots as a tool that must be maintained and used in the right circumstances and their help or hindrances depend on the situations that they are facing. Moreover, since Robots are tools, there are some limitations in their applications and LEOs should be trained regarding both technical limitations and advantages. It has been mentioned by LEOs that quick response time is a characteristic that makes use of robots more of help and could assist in facilitating specific duties of LEOs; otherwise, the robot will be more of a hindrance. LEOs described the challenges that made using the robot in law enforcement a hindrance and mentioned what is needed to tackle these challenges. Several mentioned education and training about robots as a step that needs to be taken. In addition to training, financial issues were considered a barrier to adopting robots in law enforcement. Law enforcement departments need to have access to available funding to be able to purchase this type of equipment. At the same time, it is necessary to offer lower price options for robots for smaller departments. LEOs also pointed out the public might not like interacting with a robot which decreases the robot's effectiveness in law enforcement. Therefore, it is important to familiarize society with this type of technology because in that case, both LEOs and the public will feel comfortable working with robots and trust robots. They also suggested that training children at schools would be one of the good options for familiarizing society with robots.

Attitude Study 2

In the focus group study, LEOs expressed different points of view about considering robots as a help or hindrance in their work.

More presence or exposure has been stated as the first important reason why there is a positive attitude by the public towards robot use in law enforcement. Especially kids or young adults are inclined to new technologies since most of them all have a device in their hand many hours a day and so that is something they can relate to. Therefore, according to LEOs, to increase the exposure of robots in society, it is important to interact with young people and build trust, which will open new possibilities and opportunities. A few LEOs mentioned that robots have capabilities beyond human abilities, which could be helpful in some scenarios.

LEOs mentioned that the public's attitude toward robots could be negative. They explained that some people may prefer a human to a robot and do not like to interact with a robot. This will pose a barrier to using robots in law enforcement. Also, it has been mentioned that robots can somewhat be intimidating in certain aspects. LEOs reported that robots are currently used for everyday situations but building a rapport with them is kind of out the window.

LEOs also emphasized education and training for the public to improve positive attitudes towards both law enforcement and robots. LEOs reasoned that currently there might be much misleading information regarding police. So, the first step would be educating the public about the police, how they do their job, what they are using, and what they are going to use the robot for. The public should be educated about robot use in law enforcement and how it is going to be used as a tool to help LEOs and improve their efficacy of work, safety, and also public safety. LEOs stated that using robots in law enforcement without educating the public would be very inappropriate because the public may not trust the police in some regard. This gap of understanding could be bridged with education. LEOs pointed out that schools are the best places to start public education since currently students are more exposed to new technology devices and feel comfortable working with them. Moreover, one way to do education would be asking for help from people who necessarily have influence in the community; who are outspoken in the community; or members of the media. At the same time, the training of LEOs was considered necessary by LEOs. This training could be on topics of robots, new technologies, communication skills and then also incorporate the technical aspects into LEOs' jobs. LEOs mentioned several other implementation barriers that need to be addressed, including lack of budget, cost and accuracy of new technologies.

Communication Study 1

Most LEOs in study 1 described communication via robots as good enough. Specifically, most LEOs believed communication using robots is more effective than human face-to-face communication. Many others reported that robots could provide safer communication compared to in-person communication, such as when communicating in a dangerous or barricaded situation. Moreover, robots offer functionalities such as translation and interpretation, as well as being able to communicate with disabled individuals.

Although most LEOs agreed that robots can be better at communication than in-person communication, some reported otherwise. Because of the lack of human contact, robots might not be good communicators despite the functionalities they can provide.

Communication Study 2

In the focus group study, LEOs reflected a generally positive attitude toward the communication ability of robots. In particular, it was repeatedly mentioned that robots provide more communication abilities and more information, as well as make communication more effective and convenient.

DISCUSSION

Regarding trust, most of the LEOs in both studies stated their low trust in the robot as it may fail during the operation. Another reason for this low trust could be the lack of similar communication robots already in use. Most LEOs are skeptical about embracing the new additions to the already in-use processes. Also, the reduction of face-to-face communication, which can degrade rapport, could play a crucial role in reducing LEOs' trust in the robot as it lessens the rapport between LEOs and citizens. Moreover, it is possible that robots turn against the LEOs through hacking. The type of situation is also a crucial parameter to the LEO's trust in the robot. Taking all this into account, adding new features such as online translating feature, weapon detection, emotion recognition, or improving the sensory features such as the addition of different types of cameras (e.g., thermal camera) to provide more information with higher accuracy can play a significant role in the increase of LEO's trust in communication robots. Previous research has demonstrated that the trust levels of LEOs increased following training (Bordbar et al., 2021). Consequently, there is considerable potential for their trust in robots to significantly increase with proper training and improved design.

Some LEOs had a positive attitude towards using robots as a tool in law enforcement since robots could be force multipliers; alleviate the possibility of perceived immediate danger; have capabilities beyond human abilities. Also, due to the recent advances in robotics, robots were believed by LEOs to be more accepted in the future, and this is a factor that increases LEOs' willingness to adopt robots in their work. However, others posed negative attitudes towards using robots in law enforcement and believed that robots could not be considered a good replacement for human officers since robots lack human sense and could not create a sympatric relationship with individuals. Also, the more LEOs rely on robots, the less they would have control of situations and their work which was considered one of the disadvantages of using robots. Moreover, there were some other reasons mentioned by LEOs, including robots being intimidated, expensive training on working with robots, and ethical issues using robots which pose a negative attitude towards robots. Consistent with existing literature, attitudes towards robots can be influenced by both human-related and robot-related factors (Hancock et al., 2011; Navarro et al., 2021), as well as cultural differences (Bartneck et al., 2005; Huerta et al., 2012) and self-efficacy (Latikka et al., 2019). It can be concluded that, depending on the situation, the use of robots as tools in law enforcement can be either helpful or a hindrance (Yunus & Doore, 2021; Szocik & Abylkasymova, 2021). However, training of officers and the public could solve the ambiguity and doubts regarding the benefits or drawbacks of using robots in law enforcement. Of course, this needs allocating budget to law enforcement departments in the first place to educate officers and then be able to purchase applicable robots for their work. Public education could be done with the help of community outreach and influencers.

In addition, safety was the primary focus concern of LEOs. When discussing the communication abilities of robots, LEOs envision the improvement of communication and its' ability to improve safety for officers and the public. Additionally, LEOs were hoping to use robots to gain abilities beyond human capabilities, such as practical and comprehensive interpretations. In general, LEOs trust robots' communication abilities and believe robots can assist in their work. Similarly, LEOs mentioned the safety concerns repeatedly in discussing scenarios for robot implementation. For instance, by discussing some of the common scenarios that already use robots such as bombing and hostage, LEOs were hoping to use them as a tool to reduce dangerous exposures of the officers and the public. However, many still consider robots a force multiplier that can assist them in completing repetitive or mundane tasks. Either way, robots can greatly assist LEOs in their daily tasks.

Other considerations

When introducing new technology, especially robots in law enforcement, ethical considerations are crucial. These considerations can be addressed by adhering to established standards and guidelines in both robot design and use. In a previous study, LEOs expressed awareness of ethical issues and offered suggestions for addressing them, such as ensuring control over autonomous robots and developing ethical guidelines to hold them accountable. LEOs also emphasized that robots should be used as tools, not replacements for humans, and be mindful of potential distractions and lack of personal contact. Ethical guidelines and principles have been proposed by organizations like IEEE, which has published documents to guide ethical considerations in autonomous and intelligent systems. Standards have been established to minimize unethical impacts of robots, and responsible robotics should be built on best practices that involve stakeholder participation and multidisciplinary teams to eliminate bias (Salehzadeh et al., 2022). Integrated methods combining conceptual analysis and empirical studies are recommended for analyzing the impact of robots on humans. Salehzadeh et al. (2022) suggested aggregating stakeholder opinions to align future research with ethical guidelines. Thus, this study investigated robot design and use through participatory-based design and focus group interviews to guide the ethical use and design of communication robots in law enforcement.

This study utilized experiential learning for improving robot design. Experiential learning, combined with the integration of working prototypes, has been effectively and widely utilized in teaching students about the design and practice of robots (Resnick & Silverman, 2000; Verner & Korchnoy, 2013). Learning through design not only fosters a sense of community among learners (Resnick & Silverman, 2000, 2005) but also enables designers to gain experiential knowledge. This knowledge is crucial for understanding the needs, preferences, and challenges of end-users, ensuring that robots are designed with the user in mind, leading to more intuitive and user-friendly interfaces. Incorporating experiential knowledge into the design process allows designers to consider practical aspects of robot deployment, such as environmental conditions, human-robot interaction, and task-specific requirements. This ensures that the robot is effective in real-world scenarios. Moreover, experiential knowledge can inspire innovation by highlighting unmet needs or identifying areas for improvement, leading to novel solutions and enhancements that increase the robot's effectiveness and user satisfaction. Understanding user experiences and cultural contexts is vital for creating robots that are socially acceptable and less likely to face resistance from users or the public. Additionally, experiential knowledge can inform ethical considerations in robot design, ensuring that robots respect privacy, autonomy, and other ethical principles. Therefore, incorporating experiential learning into the design process is essential for ensuring seamless collaboration between humans and robots (Northeastern University, 2024).

Limitations

Despite the positive findings, this study still has some limitations. A larger sample would benefit our results, and we were hoping most LEOs could complete the whole study. Additionally, we had to overcome some coding challenges, such as overlapped coding. For instance, the communication and trust themes. Those were often mentioned together and hard to classify into categories. Some of them might be better interpreted as a whole. Therefore, the authors conducted several meetings to discuss coding strategies. Future researchers are encouraged to confirm the definitions of the categories that could be hard to differentiate before the coding process. Lastly, opinions from the public are needed regarding robot implementation in law enforcement. The next step is to gather information from the community and the public and explore what they hope to see in a robot that can contribute to their community life.

CONCLUSION

The two studies presented offer insight into various facets of employing teleoperated robots for communication between LEOs and citizens. Currently, while LEOs exhibit low trust in these robots, there is optimism that this trust can be enhanced through education, improved robot design, and technological advancements. It is evident that LEOs' attitudes towards robots are context dependent. However, through collaborative efforts between LEOs and the public sector, these robots have the potential to enhance the safety of both parties. Future research should delve into the community's perspectives on communication robots, shedding light on their acceptance and potential integration into public safety measures.

IMPLICATION

The findings of this study offer valuable insights for future research on communication robots in police work. By considering the opinions of LEOs regarding the use of robots in law enforcement, improvements can be made in robot design, functionality, and implementation. A well-designed robot can assist LEOs in their daily tasks, thereby contributing to the development of community relationships. It is important to note that the introduction of new technology in any domain brings forth concerns such as ethics, public privacy and perception, and public safety. These concerns should be addressed at all stages of robot design and deployment.

REFERENCES

Abeykoon, I., & Feng, X. (2017). *A forensic investigation of the robot operating system.* Paper presented at the 2017 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData).

Asaro, P. (2016). "Hands up, don't shoot!" HRI and the automation of police use of force. *Journal of Human-robot Interaction*, *5*(3), 55-69.

Bartneck, C., Nomura, T., Kanda, T., Suzuki, T., & Kato, K. (2005). *Cultural differences in attitudes towards robots*. doi: 10.13140/RG.2.2.22507.34085

Bartneck, C., Nomura, T., Kanda, T., Suzuki, T., & Kennsuke, K. (2005). A cross-cultural study on attitudes towards robots. Lawrence Erlbaum Associates.

Bordbar, F., Salehzadeh, R., Cousin, C., Griffin, D. J., & Jalili, N. (2021). *Analyzing human-robot trust in police work using a teleoperated communicative robot.* Paper presented at the 2021 30th IEEE International Conference on Robot & Human Interactive Communication (RO-MAN).

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in*

Psychology, 3(2), 77-101.

Bröhl, C., Nelles, J., Brandl, C., Mertens, A., & Nitsch, V. (2019). Human–robot collaboration acceptance model: development and comparison for Germany, Japan, China and the USA. *International Journal of Social Robotics*, *11*(5), 709-726.

Brooks, D. J., Lignos, C., Finucane, C., Medvedev, M. S., Perera, I., Raman, V., Kress-Gazit, H., Marcus, M., & Yanco, H. A. (2012). *Make it so: Continuous, flexible natural language interaction with an autonomous robot.* Paper presented at the Workshops at the Twenty-Sixth AAAI Conference on Artificial Intelligence.

Bulmer, M. (1979). Concepts in the analysis of qualitative data. *The Sociological Review, 27*, 651–677.

Chanel, C. P., Roy, R. N., Dehais, F., & Drougard, N. (2020). Towards mixed-initiative human–robot interaction: Assessment of discriminative physiological and behavioral features for performance prediction. *Sensors*, *20*(1), 296.

Chen, J. Y., Durlach, P. J., Sloan, J. A., & Bowens, L. D. (2008). Human–robot interaction in the context of simulated route reconnaissance missions. *Military Psychology, 20*(3), 135-149.

Day, B., Bethel, C., Murphy, R., & Burke, J. (2008). *A depth sensing display for bomb disposal robots.* Paper presented at the 2008 IEEE International Workshop on Safety, Security and Rescue Robotics.

Flann, N. S., Moore, K. L., & Ma, L. (2002). A small mobile robot for security and inspection operations. *Control Engineering Practice, 10*(11), 1265-1270.

Freedy, A., DeVisser, E., Weltman, G., & Coeyman, N. (2007). *Measurement of trust in human-robot collaboration.* Paper presented at the 2007 International symposium on collaborative technologies and systems.

Gasser, G. (2021). The dawn of social robots: Anthropological and ethical issues. *Minds and Machines, 31*, 329–336.

Gong, L., Gong, C., Ma, Z., Zhao, L., Wang, Z., Li, X., Jing, X., Yang, H., & Liu, C. (2017). *Real-time human-in-the-loop remote control for a life-size traffic police robot with multiple augmented reality aided display terminals.* Paper presented at the 2017 2nd International Conference on Advanced Robotics and Mechatronics (ICARM).

Guest, G., MacQueen, K. M., & Namey, E. E. (2012). *Applied thematic analysis*. Sage.

Hancock, P. A., Billings, D. R., Schaefer, K. E., Chen, J. Y., De Visser, E. J., & Parasuraman, R. (2011). A meta-analysis of factors affecting trust in human-robot interaction. *Human Factors, 53*(5), 517-527.

Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors, 57*(3), 407-434.

Howard, A., & Borenstein, J. (2018). The ugly truth about ourselves and our robot creations: The problem of bias and social inequity. *Science and Engineering Ethics, 24*(5), 1521-1536.

Huerta, E., Glandon, T., & Petrides, Y. (2012). Framing, decision-aid systems, and culture: Exploring influences on fraud investigations. *International Journal of Accounting Information Systems, 13*(4), 316-333.

Javaid, M., Haleem, A., Vaishya, R., Bahl, S., Suman, R., & Vaish, A. (2020). Industry 4.0 technologies and their applications in fighting COVID-19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 14*(4), 419-422.

Karthikeyan, R., Karthik, S., TR, P. V., & Vignesh, S. (2015). *Snitch: Design and development of a mobile robot for surveillance and reconnaissance.* Paper presented at the 2015 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS).

Latikka, R., Turja, T., & Oksanen, A. (2019). Self-efficacy and acceptance of robots. *Computers in Human Behavior, 93*, 157-163.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors, 46*(1), 50-80.

Matthies, L., Xiong, Y., Hogg, R., Zhu, D., Rankin, A., Kennedy, B., Hebert, M., Maclachlan, R. ., Won, C., Frost, T., Sukhatme, G., McHenry, M., & Goldberg, S. (2002). A portable, autonomous, urban reconnaissance robot. *Robotics and Autonomous Systems, 40*(2-3), 163-172.

Mavridis, N. (2015). A review of verbal and non-verbal human–robot interactive communication. *Robotics and Autonomous Systems, 63*, 22-35.

Motaleb, A. K. B., Hoque, M. B., & Hoque, M. A. (2016). *Bomb disposal robot.* Paper presented at the 2016 International Conference on Innovations in Science, Engineering and Technology (ICISET).

Murphy, R. R. (2004). Human-robot interaction in rescue robotics. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 34*(2), 138-153.

Nath, A., Arun, A., & Niyogi, R. (2019). A distributed approach for road clearance with multi-robot in urban search and rescue environment. *International Journal of Intelligent Robotics and Applications, 3*(4), 392-406.

Navarro, J., Allali, S., Cabrignac, N., & Cegarra, J. (2021). Impact of pilot's expertise on selection, use, trust, and acceptance of automation. *IEEE Transactions on Human-Machine Systems, 51*(5), 432-441.

Nguyen, H. G., Farrington, N., & Pezeshkian, N. (2004). *Maintaining communication link for tactical ground robots*. Space and Naval Warfare Systems Center, San Diego, Ca.

Northeastern University. (2024). *Northeastern's institute for experiential robotics: Integrating human experience into the design and development of autonomous and robotic systems to ensure seamless collaboration*. https://robotics.northeastern.edu/

Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic analysis: Striving to meet the trustworthiness criteria. *International Journal of Qualitative Methods, 16*(1), 1609406917733847.

Parasuraman, R., & Manzey, D. H. (2010). Complacency and bias in human use of automation: An attentional integration. *Human Factors, 52*(3), 381-410.

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors, 39*(2), 230-253.

Park, E., Jenkins, Q., & Jiang, X. (2008). *Measuring trust of human operators in new generation rescue robots.* Paper presented at the Proceedings of the JFPS International Symposium on Fluid Power.

Patel, D. S., Mishra, D., Pandey, D., Sumele, A., & Rathod, I. (2013). Mobile operated spy robot. *International Journal of Emerging Technology and Advanced Engineering (IJETAE)*.

Rastogi, N., Keshtkar, F., & Miah, M. S. (2018). *A multi-modal human robot interaction framework based on cognitive behavioral therapy model.* Paper presented at the Proceedings of the Workshop on Human-Habitat for Health (H3): Human-Habitat Multimodal Interaction for Promoting Health and Well-Being in the Internet of Things Era.

Resnick, M., & Silverman, B. (2000). On designing technologies for children: Learning technologies with design communities. *Journal of Learning Sciences, 9*(1-2), 115-152.

Resnick, M., & Silverman, B. (2005). Some reflections on designing construction kits for kids. In *Proceedings of the 2005 conference on Interaction design and children* (pp. 117-122).

Royakkers, L., & van Est, R. (2015). A literature review on new robotics: Automation from love to war. *International Journal of Social Robotics, 7*(5), 549-570.

Salehzadeh, R., Bordbar, F., Griffin, D. J., Cousin, C., & Jalili, N. (2022, August). Public Perception, Privacy, Safety, and Ethical Considerations of Communication Robots in Law Enforcement. In *2022 31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)* (pp. 1586-1591). IEEE.

Salvini, P., Ciaravella, G., Yu, W., Ferri, G., Manzi, A., Mazzolai, B., Laschi, C., Oh, S. R., & Dario, P. (2010). *How safe are service robots in urban environments? Bullying a robot.* Paper presented at the 19th international symposium in robot and human interactive communication.

Szocik, K., & Abylkasymova, R. (2021). Ethical issues in police robots. The case of crowd control robots in a pandemic. *Journal of Applied Security Research*, 1-16.

Theodoridis, T., & Hu, H. (2012). Toward intelligent security robots: A survey. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 42*(6), 1219-1230.

Verner, I. M., & Korchnoy, E. (2013). Experiential learning through designing robots and motion behaviors: A tiered approach. *International Journal of Engineering Education*, *22*(2), 222-232.

Vogeley, K., & Bente, G. (2010). "Artificial humans": Psychology and neuroscience perspectives on embodiment and nonverbal communication. *Neural Networks*, *23*(8-9), 1077-1090.

Yunus, A., & Doore, S. A. (2021). *Responsible use of agile robots in public spaces.* Paper presented at the 2021 IEEE International Symposium on Ethics in Engineering, Science and Technology (ETHICS).

Zeng, J., Yang, R., Zhang, W., Weng, X., & Qian, J. (2007). Research on semi-automatic bomb fetching for an EOD robot. *International Journal of Advanced Robotic Systems, 4*(2), 27.

Zheng, C. (2019). *Mechanical design and control system of a miniature surveillance robot.* Paper presented at the 2009 International Conference on Information and Automation.

Authors' Note

All correspondence should be addressed to
Xiaoti Fan
Department of Communication Arts,
The University of Alabama in Huntsville, 35899
xiaoti.fan@uah.edu

Acknowledgments

The authors would like to thank Dr. Richard Davis, who is a criminal justice professor at Jacksonville State University, as well as the law enforcement administrators and officers who supported and participated in this study for their perspective and efforts. Additionally, we would like to thank Andrew Laningham and Glen Merritt for their assistance in exporting the focus group transcripts.

Funding Statement

This research is supported by the National Science Foundation under Award No. 2026658. Any opinions, findings, and recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the sponsoring agency.

Disclosure

This paper discusses the findings on LEOs' perspectives and attitudes towards communication robots. However, we fully acknowledge and value the perspectives of the civilians and the community that are impacted by the integration of robotic technology in law enforcement. Therefore, one of the future aims of this research project is to obtain and gather feedback from the public domain and various stakeholder communities in order to promote safety for both the LEOs and the civilians.

Moreover, it has been and will be our team's utmost priority to guarantee the confidentiality and privacy of all persons engaged in our technology development through proper approaches in consultation with privacy experts. In addition, our team acknowledges that a diverse array of perspectives and feedback from all community classes should be obtained, especially when inequality and inequity may exist. Our diverse research team consists of international and domestic scholars from marginalized communities, working-class people, and people of color who consistently discuss the needs of these communities and possible unintended consequences and potential impacts of these tools.

Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology
ISSN: 1795-6889
https://ht.csr-pub.eu
Volume 20(1), May 2024, 45-69

AN EMPIRICAL STUDY ON EMAIL USE, STRESS, AND EMPLOYEE JOB SATISFACTION

David J. Bouvier
DePaul University
USA
ORCID 0009-0000-3038-1383

Esther J. Hwang
DePaul University
USA
ORCID 0009-0003-7924-623X

Yujong Hwang
DePaul University
USA
ORCID 0000-0001-7323-6127

Abstract: *Technological advances continue to create efficiencies in all areas of our lives. One medium dominates above all other technological applications is electronic mail (email). As email functionality expands, so does the volume and differing responsibilities resulting in substantial increase in time and resources dedicated to email use and proposed causation of many unintended consequences. The immense volume of email has exploded, often crippling users and demanding an excessive quantity of time allocation necessary to read and respond, causing inefficiencies affecting job satisfaction resulting in decreasing performance and productivity. The year 2020 introduced COVID-19 into all aspects of our lives forcing a majority of the population to work remotely increasing our reliance on technology. Findings from business surveys suggest that email traffic is consuming an proportion of the working day which has been associated with over-monitoring, workflow disruption, work-life conflict and addition to email – all which in turn are associated with higher levels of work-related stress. Why did the revolutionary technological ability of email transform our feelings concerning it use from inspiration to an invasive essential necessity of our everyday workload? To respond to this question, we examine the effects of email volume on job satisfaction, moderated by stress, and propose a cost effective, efficient, pragmatic experiment to reduce email volume and bring greater realization to the need of controlling email volume resulting in greater job satisfaction.*

Keywords: *electronic mail; email management; job satisfaction; stress; perceived usefulness; perceived ease of use.*

DOI: https://doi.org/10.14254/1795-6889.2024.20-1.3

INTRODUCTION

Email has been studied by academia for a variety of constructs such as content, volume, usage and its effects, how often we respond, how quickly we respond, the distraction effects, addiction and stress. Email has demonstrated unprecedented diffusion in the business world since the internet became ubiquitous. Email is essentially a communication mechanism originally anticipated to purely speed up communication by replacing the slower traditional paper-based system (Jackson, Dawson & Wilson. 2003). Email creates an immense number of organizational benefits, including the ability to create timely information and information permanency, as well as increasing information accuracy and colleague interaction (O'Kane & Hargie, 2007). Yet, there is also a point where the volume of email reception produces a decreasing rate of return for the user. For example, a recent 2018 study examined the effect of overflow on cognitive performance, cognitive load, and stress, indicating that cognitive overload affects not only the execution of the task at hand, but can also negatively affect performance on subsequent, cognitively challenging activity (Nowak et al., 2018).

The sheer volume of emails received daily is a known and commonly understood problem. Over the last decades, some individuals have seen the number of daily emails grow from 50-100 to over 1000. Email overload arises so that rather than be beneficial, email may be detrimental to the productivity of both individuals and organizations (Sumecki, Chipulu & Ojaiko, 2011). On average 29% of emails that an employee receives is of no value to them (Jackson, Burgess & Edwards, 2006). While roughly 281 billion emails were sent and received each day in 2018, the figure is expected to increase to over 347 billion daily emails by 2022 (Clement, 2019). Individuals in both industry and academia allot an immense quantity of time on managing their email box. Email absorbs a high percentage of our productive time further emphasizing the necessity of assuring efficient use of this important tool. The volume has huge cost implications, both organizationally and personally. To support the volume of email, organizations spend up to $17 billion annually (Radicati Group, 2007).

Computer operating systems complexities increase resulting in expanded programming for email communication and notification. Operating system send automated emails consisting of data deemed relevant to those responsible for the programming. Once these auto emails are in place, they are rarely reviewed for relevance, need and accuracy. The purpose of this research procures an internal experiment which intends to reduce unnecessary communication through email communications. A systematic review of automated emails stemming for pre-programed operating system may have a substantial effect on email reduction resulting in increased efficiency job satisfaction.

LITERATURE REVIEW

Job Satistfaction

Overall job satisfaction is likely to reflect the combination of partial satisfactions related to various features of one's job, such as pay, security, the work itself, working conditions, working hours and the like (Skalli, Theodossiou & Vasileiou, 2008). Job satisfaction is fundamentally the overall feeling one derives from their job. A multitude of variables that comprise the overall satisfaction of a job satisfaction do vary amongst individuals. Job satisfaction is multi-dimensional which is compatible with the view that there are partial satisfactions arising from different aspects of the job that occupy different points on the scale of satisfaction. The overall job satisfaction or utility derived from a job is an aggregation of these partial satisfactions. Different mix of facets of the job may generate the same overall level of job satisfaction (Skalli et al., 2008).

Job satisfaction is an important construct that can affect an employee's ability to perform at their highest level of productivity. The level of job satisfaction can have a profound impact on the effectiveness and efficiency of employees and may have a significant effect on the firm financially. Increasing overall job satisfaction in a company can improve an organizations workforce efficiency creating a competitive advantage. According to the scientists of human resource management, in order to maintain human resources (satisfaction) and also the organization itself (achieving organizational goals), it is of prime importance to recognize the needs, desires and factors such as job satisfaction, employee's morale as well as to make appropriate policy for the coordination of individual's goals (employee's job satisfaction) and organizational goals as an important step towards efficiency and effectiveness of organizations performance (Masihabadi et al., 2015).

An employee's level of job satisfaction has been linked to stress. A 2011 study on 210 managers from different private sectors examined the role of stress and focus of control on job satisfaction. The findings revealed overall stress was significantly negatively correlated to job satisfaction (Singh & Dubey, 2011). A 2010 study with a sample of 150 school administrators revealed that about one-fifth of the respondents classified their job as very or extremely stressful. The results also showed those with greater stress levels were least satisfied with their role (Borg & Riding, 1991). A famous researcher Vroom (1964) supported in his research study that the concept of job satisfaction affects the performance of an employee positively, his work was based on the thought the natural product to fulfills the needs of employees is their performance (Hassan et al., 2020).

Stress

The term 'stress' is basically from physical science, where it means the force placed upon an object to cause damage, bending, or breaking. In the case of human beings, stress is often used to describe the body's responses to demands placed upon it, whether these demands are favorable or unfavorable. Anything that causes stress is called a stressor. (Rekha & Paramanandam, 2017). The pioneering idea about job stress concept came from Seyle (1936). Excess stress for a long time period is not good for employees. Stress has impacted virtually all professions, beginning from a general worker to a doctor, or an engineer to a sales personnel and obviously increased stress directs towards quitting the job (Ahmad & Afgan, 2016). Stress is one of the pervasive problems of an organization. For an institution to prosper, it is prerequisite that its employees work in a stress-free ambiance. It leads to decrease in employees' efficiency, increase in absenteeism and turnover (Ahmed, Warraich, Khoso & Ahmad, 2014). In the current era, stress has turned out to be a worldwide phenomenon faced by large number of employees around the globe (Ahmad et al., 2016).

The relationship to between stress and email has provided a strong correlation in studies. The majority of email stress literature to date is concentrated within the business and information technology domains (Schuldt & Totten, 2008). Pignata's (2015) study had a population of academic and professional staff, it assessed the stress level created by email volume and response time expectations theorizing the creation of a common framework for employee email use will clarify expectations and increase efficiency. Communication and interpersonal relationships increased team cohesion when use of email communication was decreased and simplified. Ramsey's (2012) qualitative interview study reinforced stress feelings over email volume decreased productivity. Jerejian (2013) evaluated an academic population and emphasized stress and worry associated with high email volume resulted in lower employee efficiency. Early studies such as Whittaker and Sider's (1996) study examined a "one touch model" on white-collar workers which hypothesized that all email would be read, filed then deleted, and result in reduced stress. Jerejian, Reid and Rees (2013) examined the relationship between worry and email stress. The study showed individuals who had a higher degree of stress in their job, or life, had higher level of anxiety when email volume increased as opposed to those who are less stressed. Stress created by email use is pervasive throughout varying business and academic users.

Technology Acceptance

The technology acceptance model (TAM) examines the causal relationship between behavioral intention to use technology and actual use (Hwang, 2008, Hwang, 2016). The TAM model further breaks down two important components of primary relevance, perceived usefulness (PUSE) and perceived ease of use (PEOU). PUSE is the perception of an individual that using technology will improve job performance. PEOU is an individual's degree of ease in using technology. Yi & Hwang (2003) found a direct and significant influence of behavioral intention to use on actual system usage log data ($P<.05$) in the Web-based IS environment (Hwang, 2005).

Individuals who lack confidence in electronic communication also showed significantly lower performance and higher stress (Tassabehji, 2005, Hwang, Kettinger & Yi, 2015). The amount of email volume may have a moderating effect on the differing levels of technology acceptance in relation to job satisfaction. In technology adoption context, the key behavior of interest is use of the system; therefore, attitude toward behavior is a potential users' affective evaluation of the costs and benefits of using the new technology (Morris & Venkatesh, 2000, Hwang, Kettinger & Yi, 2013). The importance of computer use and associated applications was apparent during COVID as our reliance increased dramatically. An employee's comfort in computer applications may have an increased effect on their ability to perform job responsibilities from remote locations.

Email Volume Perception

Email was invented by Ray Tomlinson, which first entered limited use in the 1960s, by the mid-1970s electronic mail delivery developed into the form we now recognize as email. Usage was originally limited to low volume until legislation passed in 1995 which gave allowance to commerce. Email's ease of information sharing, and simple document transfer capabilities created many efficiencies and are adopted throughout business, academia, and personal use. Email's pervasiveness as a form of organizational communication can be attributed to its advantages such as asynchrony and flexibility, which facilitate rapid and widespread information sharing among employees (Barley, Meyerson & Grodal, 2011; Byron, 2008). Email is an essential tool in business and academic environments. The complexity of tasks that may be accomplished with its use has created enormous opportunities for sharing information, communicating, and linking individuals and groups.

Research on email conducted in the past two decades discussed many aspects of its multipurpose usage. For example, a study of 875 individuals reported on average 29% of the email received were of no value to them (Jackson, 2006). This study found that 41% percent of emails were for informational purposes and only 46% of emails received stated what action is expected. The data exemplifies employee dissatisfaction with the use of email within their workplace and estimated expense of these inefficiencies' costs companies in excess of 8%. The numbers from the Jackson 2006 study represent an email volume that is drastically lower than the current levels experienced in academic and company environments, thus the 8% inefficiency estimate may be understated.

Academia research proposes two main veins of email research. One vein of research examines the availability and accessibility of email on our electronic devices causing work to carry over into personal and family time. The ability to view email from our home computer or smart phones, combined with the expectations of a response to the sender, infringes on personal time and space. These studies rest on variants of the argument that email, and other communication technologies produce stress by enabling work to leak into other domains of life, thereby extending work hours and making it more difficult to disengage from work and fulfill family obligations (Barley et al., 2011; Major, 2002; Bosweel & Olson-Buchanan, 2007).

Email overload is the second vein of research. Barleys (2011) states there are four main occurrences that creates additional work from email resulting in feelings of stress. First, since email is simple and easier to send than letters and memos, more time must be spent on sorting and filing the message. Second, the low costs and time needed to make email requests from the sender diverts time from the receiver to take care of current tasks. Third, email interruption causes inefficiencies in concentration on tasks at hand. Fourth, email is used for tasks that it was not designed to handle. The common dominator that cuts across the two foregoing bodies of research is that email and other communication technologies induce stress by extending the time that people work, but the explanation differ (Barley et al., 2011). Email overload arises so that rather than be beneficial, email may be detrimental to the productivity of both individuals and organizations (Sumecki, Chipulu & Ojaiko, 2011). On average 29% of emails that an employee receives is of no value to them (Jackson, Burgess & Edwards, 2006). Individuals in both industry and academia allot an immense quantity of time to managing their email box. Email absorbs a high percentage of our productive time further emphasizing the necessity of assuring efficient use of this important tool. The high volume has huge cost implications, both organizationally and personally. To support the volume of email, organizations spend up to $17 billion annually (Radicati Group, 2007).

Even though the principle of email management has been the cause for concern since email was created, the effect of email on human behavior has only recently been recognized as an urgent call for concern (Maruland-Carter & Jackson, 2012). The previous statement was written ten years prior, yet we fail to recognize the need for optimization of our emails systems and habits today. Findings from business surveys suggest that email traffic is consuming an increasing proportion of the working day which has been associated with over-monitoring, workflow disruption, work-life conflict and addiction to email – all of which in turn are associated with higher levels of work-related stress (Barley et al., 2011; Cooper, 2005; Dabbish & Kraut, 2006; Hair, Renaud, & Ramsay, 2007; Hill, Hawkins, Ferris, & Weitzman, 2001). Work-life habits have continued to shift, and the COVID environment has enabled many employees to work entirely from home, further blurring the line between work and home life. Email volume continues to plague employees and is an area of great concern. An employee's perception of email volume may be just as important than the actual email volume due to the psychological effects of the perception.

HYPOTHESIS DEVELOPMENT

To date, no study has looked specifically at stress, PUSE and PEOU, combined with a newly introduced automated email reduction program and its effect on job satisfaction. A core element for employee productivity is job satisfaction. The relationship is established in research correlating job satisfaction to many facets of the work environment. If employees in the company are not satisfied with his job then they are unable to do their job as per their estimated norms and expectations (Hassan, Azmat, Sarwar, Adil & Gillani, 2019; Adebimpe, 2013). During COVID, the economy was forced to change its core functionality abruptly. The imposed shut down may have created new stressors on our population.

The "stay at home" mandate that thrust the labor force into a remote work life placed unprecedented levels of dependance on electronic communication. IT departments were asked to create a work environment that simulated day to day office operations. Many industries had little exposure to remote work. All companies, industries, and establishments retooled their operations to accommodate the new societal norm. Technology is the key component utilized to accommodate this transition. The comfort of an individual's ease of use of technology, as well as the perceived usefulness can affect the success of an employee's transition. The reliance on technology did introduce new mediums into the mainstream work process. For example, local employees who previously met in office conference rooms, were now meeting remotely through online mediums, such as Zoom. Transitioning to unfamiliar technology was imperative and immediate, forcing all users to shift to a total reliance on the new mediums. The TAM constructs, PUSE and PEOU measure this aptitude and are an important relationship to job satisfaction.

The reliance on technology also placed greater emphasis on existing applications. Email usage continues to grow along with new mediums that further place demands on users. Email was originally designed as a communication application, but is now being used for additional functions that it is not designed for, such as task management (Whittaker & Sidner, 1996). The pandemic may lead to an increase in email volume, which is already a burden. To reduce the effects resulting from the pressure of remote work and electronic communication, this research has implemented a program to create a systematic reduction of automated emails, accomplished with minimal cost or disruption of daily responsibilities. Successful implementation may create a competitive advantage to firms applying this tool effectively.

The changing environment may create additional stressors in employees as they move to remote based locations. The transition utilized technology-based methods to communicate and perform job responsibilities, the degree to which employee's embrace the technology use is considered. The perception of the degree in which email volume changes is of importance. Given the information described above, the purpose of this research is to examine the relationship between job satisfaction, stress, PUSE, PEOU and perceived automated email volume.

Hypothesis 1 – PUSE has a positive effect on job satisfaction.

Hypothesis 2 – PEOU has a positive effect on job satisfaction.

Hypothesis 3 – perceived automated email reduction will have a moderating effect on the relationship between job stress and job satisfaction.

Hypothesis 4 – perceived automated email reduction will have a moderating effect on the relationship between PUSE and job satisfaction.

Hypothesis 5 – perceived automated email reduction will have a moderating effect on the relationship between PEOU and job satisfaction.

METHODS

The method is a quantitative design using validated survey measures to assess the correlation effects on job satisfaction (DV) due to stress (IV) and technology acceptance (IV), moderated by perceived automated email reduction program. A task force was assembled to analyze and reduce the number of automated emails sent out to employees from the loan operating system. Emails were assessed for necessity, recipient list, and content. Employees were given notification of the program which took place over 12 months. Upon completion of the program, an anonymous survey was provided for analysis. The validated survey measures were statistically analyzed using SPSS, and reliability is assessed with Cronbach's alpha reliability. The descriptive statistics including mean, standard deviation, reliability, and correlations are displayed in Table 1. Tables 2, 3 and 4 display the ANOVA factor analysis results for the interactions. The experiment intention is to establish covariation of cause on job satisfaction from stress, PUSE, and PEOU while moderated by perceived email volume reduction. Plausible alternative explanations for significance in the relationship are considered in the limitations analysis section. The correlation study establishes the groundwork for action research using modest employee interference through the simple reduction of automated emails to moderate the effect of stress and technology acceptance on job satisfaction.

Table 1. Collective data of control constructs

Construct		Number	Percentage
Gender	Male	104	70.75%
	Female	43	29.25%
Age	18-29	16	10.88%
	30-39	32	21.77%
	40-49	34	23.13%
	50-59	38	25.85%
	60+	27	18.37%
Job Type	Assistant	21	14.29%
	Executive	3	2.04%
	Manager	20	13.61%
	Loan Officer	45	30.61%
	Processor	20	13.61%
	Operations	32	21.77%
	Compliance	2	1.36%
	Post Closing	3	2.04%
	Finance	1	0.68%

Table 2. Survey items

Survey Items

Likert scale from 1 - 5

Construct	Scale Items	Adapted From
Satisfaction	Generally speaking I am very satisfied with this job	Hackman et al., 1975
	I usually know whether or not my work is satisfactory on this job	
	I feel unhappy when I discover that I have performed poorly on this job	
	The work I do on this job is very meaningful	
	My opinion of myself goes up when I do this job well	
	I sometimes think of quitting this job	
Stress	In the last month how often have you felt you were on top of things?	Cohen et al., 1989
	In the last month, how often have you been angered because of things were outside of your control?	
	In the last month, how often have you felt you could not cope with all the things that you had to do?	
	In the last month, how often have you felt that things were going your way?	
	In the last month, how often have you been able to control irritations in your job?	
PUSE	I find computers easy to use	Davis, 1989
	I find it easy to get computers to do what I want it to	
	My interaction with computers is clear and understandable	
	Using computers improves my work	
	Using computers enhances my effectiveness	
PEOU	Using computers increases my productivity	Davis, 1989
	I have trouble finding the information I need in work-related emails, text, etc.	
	I have difficulty dealing with the amount of work-related electronic communications I receive.	
	I sometimes miss information or important work-related electronic communications messages.	
	Dealing with my work-related electronic communications disrupts my ongoing work.	

Table 3. Means, Standard Deviations, Reliabilities, and Correlation Matrix

Variable	Mean	SD	1	2	3	4	5	6	7	8
1.Job Satisfaction	4.41	.55	*. 57*							
2. PUSE	4.56	.80	.28**	*.90*						
3. PEOU	2.79	.07	-.17*	-.21**	*.86*					
4. Job Stress	3.86	.83	-.32**	.16*	-.41**	*.82*				
5.COVID email	3.94	.97	.14	.11	.98	-.11	*.56*			
6. Job type	4.15	1.84	.07	-.10	-.01	.06	-.07	-		
7. Gender	1.29	.46	-.12	-.13	.11	.07	.07	.05	-	
8. Age	48.14	12.55	-.19*	-.30**	-.21**	-.09	-.12	-.01	.12	-

Note. N = 147
[1] Alpha reliability appears in the diagonal
* $p < .05$
** $p < .01$

Table 4

Model 1	β	Standard Error	*t*
Constant	5.47	.26	21.06
JOB	0.02	.02	1.02
Male-Female	-.19*	.09	-1.98
AGE	-.01*	.00	2.16
Jstress	-.27**	.07	-3.91
N= 147		F(4,142) = 6.4, p < .01	
* $p < .05$	R^2 =	0.15	
** $p < .01$			

Model 2	β	Standard Error	*t*
Constant	3.68	.48	7.73
JOB	.03	.02	1.43
M-F	-0.12	.09	-1.28
AGE	-0.01	.00	-1.55
PUSE	.22**	.07	2.90
N= 147		F(4,142) = 4.58, p < .01	
* $p < .05$	R^2 =	0.11	
** $p < .01$			

Model 3	β	Standard Error	*t*
Constant	4.99	.57	4.38
JOB	.30	.02	1.32
M-F	-.15	.09	-1.89
AGE	-.01*	.00	-1.29
PEOU	-.06	.08	2.23
N= 147		F(4,142) = 2.90, p < .05	
* $p < .05$	R^2 =	0.08	
** $p < .01$			

Table 5

Model 1	β	Standard Error	*t*
Constant	4.41**	0.05	99.00
JOB	0.03	.02	1.24
M-F	-0.16	.09	-1.65
AGE	-.01*	.00	-2.44
N= 147		F(3,143) = 3.125, p < .05	
* $p < .05$	R^2 =	0.06	
** $p < .01$			

Model 2	β	Standard Error	*t*
Constant	4.41**	0.04	105.42
JOB	0.03*	0.02	1.16

M-F	-0.20	0.09	-2.20
AGE	-0.01	0.00	-1.88
COVID center	0.1*	0.04	2.31
Stress center	0.29**	0.07	4.24
N= 147		F(5,141) = 6.35, p < .01	
* *p* < .05	R^2 =	0.12	
** *p* < .01		*Change in R^2 = .12*	
		Change in F(2,141) = 10.55, p < .01	

Model 3	**β**	**Standard Error**	***t***
Constant	4.41**	0.04	104.82
JOB	0.03	0.02	1.11
M-F	-0.21*	0.09	-2.29
AGE	-0.01	0.00	-1.88
COVID center	0.1*	0.05	2.22
Stress center	0.29**	0.07	4.26
COVID Stress Int	0.05	0.06	0.82
N= 147		F(6,140) = 5.39, p < .01	
* *p* < .05	R^2 =	0.14	
** *p* < .01		*Change in R^2 = .004*	
		Change in F(1,140) = 4.47, p > .05	

Table 6

Model 1	**β**	**Standard Error**	***t***
Constant	4.41**	0.05	99.00
JOB	0.03	.02	1.32
M-F	-0.16	.09	-1.89
AGE	-.01*	.00	-1.29
N= 147		F(3,143) = 3.125, p < .05	
* *p* < .05	R^2 =	0.06	
** *p* < .01			
Model 2	**β**	**Standard Error**	***t***
Constant	4.41**	0.04	101.90
JOB	0.03	0.02	1.52
M-F	-0.14	0.09	-1.41
AGE	-0.01	0.00	-1.43
COVID center	0.07	0.05	1.44
PUSE center	0.21**	0.08	2.78
N= 147		F(5,141) = 4.11, p < .01	
* *p* < .05	R^2 =	0.13	
** *p* < .01		*Change in R^2 = .07*	
		Change in F(2,141) = 5.31, p < .01	
Model 3	**β**	**Standard Error**	***t***
Constant	4.41**	0.04	102.73
JOB	0.03	0.02	1.34
M-F	-0.12	0.09	1.27
AGE	-0.01	0.00	-1.91
COVID center	0.07	0.05	1.49
PUSE center	0.09	0.09	0.911
COVID PUSE Int	-0.15*	0.07	-2.12
N= 147		F(6,140) = 4.26, p < .01	
* *p* < .05	R^2 =	0.15	
** *p* < .01		*Change in R^2 = .027*	
		Change in F(1,140) = 4.47, p < .05	

Sample

The sample consists of 147 bank employees at a publicly traded mid-sized southern regional bank with approximately 1,800 employees. The sample population is comprised of employees in the lending division that rely on technology as a vital tool to complete their responsibilities throughout the workday. The sample group uses technology, including email, throughout the day and typically have easy accessibility to all work-related information through both company and personal devices. Examples of the population that may represent the generalizability of these samples are institutions such as banks, universities, insurance, technology, consulting, and accounting.

Procedure

A task force of bank employees was created to examine automated emails produced through the loan operating system. The task force consisted of nine individuals representing different divisions as well as two senior officers. The responsibilities of the task force are to examine all automated emails for necessity, relevance, and content. The four stated goals are (1) email overall necessity, (2) check for redundancy or duplicate emails, (3) verify email is delivered to intended recipients, and (4) check to assure the email communication is clear for its intended purpose. Task members were assigned emails to review with the intended recipients, recipients' managers, and department managers to evaluate in regard to the task force objectives. The task member then discusses all recommendations with the department manager. Once the department manager and task member come to an agreement on the recommended changes, it is presented to the task force to finalize approval. Upon approval by the task force, final "signed" authorization is provided by the task force senior manager. The emails are either removed, left as is, or the recipients and verbiage is updated, then provided to IT for implementation.

The task force evaluated 372 automated emails from the loan operating system. The emails were divided in 13 sprints, each contained 28-30 emails for evaluation. The task force met every 2 to 4 weeks to assess current progress and approval of recommended email changes. Upon completion of all emails in a sprint, a new sprint would be assigned to members according to their department for the email target participants. An audit trail was used to keep track of all changes in the email recipients as well as any verbiage changes. The entire process took place over a 12-month period. Of the 372 emails, 31 were retired and deemed completely unnecessary. Recipients were changed on 46 emails, and verbiage was revised on 51 emails.

After the task force email changes were complete, an anonymous survey was sent to employees through email. Of the 387 employees that received the survey link, 147 completed the survey in its entirety. Employees were aware of the ongoing email reduction program throughout the year. When the program began, most employees of the loan department were already working remotely due to the COVID environment. As of January 2022, over 40% of the workforce that had previously worked in the office were now predominantly working remotely.

Measures

The dependent variable is job satisfaction, the independent variables are stress, PUSE, and PEOU moderated by PMail with the control constructs of age, gender, and job type. The survey was provided through an internal email containing brief instructions to the anonymous survey link. The link provides a secure connection to the confidential Qualtrics survey platform, upon link establishment, detailed instructions for completion were provided. The survey utilizes the five-point Likert scale (1 = never, 5 = often, for performance questions, 1 = strongly disagree, 5 = strongly agree for remaining questions). All scores are averaged to create a composite score to better comprehend the degree of the underlying constructs. The survey begins with age, gender, and job type, then proceeds to PUSE, PEOU, job satisfaction, and concludes with stress questions. Validation questions are administered throughout of the survey. Table 1 presents the collective profile of the control construct data. The survey questions were researched and selected from validated measures detailed below and found in Table 2. Detailed descriptions of the measurement items are shown below.

Job Type - Executive, Management, Loan Officer, Loan officer support, Processor, Assistant, Loan Operations, Compliance, Post Closing, Technology, Secondary/Finance
Stress - Stress is measured with the Perceived Stress Scale (PSS), validated shorter version of the 14-item scale (Cohen & Williamson, 1988). Items are rated on a 5-point scale (1 = never, 5 = often). The higher the composite score the greater the perceived stress the individual is experiencing. Scale items include: “In the last month how often have you felt you were on top of things?” “In the last month, how often have you been angered because of things were outside of your control?” “In the last month, how often have you felt you could not cope with all the things that you had to do?” “In the last month, how often have you felt that things were going your way?” “In the last month, how often have you been able to control irritations in your job?”
Technology Acceptance (PUSE & PEOU) - TAM has proven to be among the most effective models in the information systems literature for predicting user acceptance and usage behavior. The original instrument for measuring these beliefs was developed and validated by Davis (1986; 1989; 1993), and Davis et al., (1989), and replicated by Adams, Nelson and Todd (1992), Mathieson (1991), Hendrickson, Massey, and Cronan (1993), and Segars and Grover (1993). The instrument has also been used extensively by researchers investigating a range of issues in the area of user acceptance (Moore & Benbasat, 1991; Olfman & Bostrom, 1991; Trevino & Webster, 1992; Chin & Gopal, 1993; Sjazna, 1994; Venkatesh & Davis, 1994; Davis & Venkatesh, 1995; Taylor & Todd, 1995). The Items are rated on a 5-point scale (1 = never, 5 = often). PUSE scale items include: “I find computers easy to use. I find it easy to get computers to do what I want it to.” “My interaction with computers is clear and understandable.” “Using computers improves my work. Using computers enhances my effectiveness.” “PEOU scale items include: Using computers increases my productivity.” “I have trouble finding the information I need in work-related emails, text, etc.” “I have difficulty dealing with the amount of work-related electronic communications I receive.” “I sometimes miss information or important work-related electronic communications messages.” “Dealing with my work-related electronic communications disrupts my ongoing work.”

Job Satisfaction (DV) - To consider the job satisfaction construct, we employ the "Affective Responses to the Job" questions of the validated survey "Development of the Job Diagnostics Survey" (Hackman & Oldham, 1975) – This is Task & work Design for JOB sat. Items are rated on a 5-point scale (1 = never, 5 = often). The higher the composite score the greater the job satisfaction the individual is experiencing. Scale items include: "Generally speaking, I am very satisfied with my job." "I usually know whether my work is satisfactory on this job." "I feel unhappy when I feel I have performed poorly on this job." "The work on do on this job is very meaningful." "My opinion of myself goes up when I do this job well." "Sometimes I think of quitting this job."

Automated email volume perception - Survey postulating questions on perceived email volume during the COVID environment. The information is a self-reported measure derived from the survey questions.

DATA ANALYSIS AND RESULTS

Quantitative data analysis utilized SPSS Statistics 28.0 software. Moderation analysis utilized unstandardized centered variables and interaction effects using hierarchical regression. The correlation matrix (Table 3) provides summary of the survey results. Job satisfaction resulted with a mean of 4.41 and a standard deviation of .55, representing a high level of job satisfaction in the company. The reliability coefficient of .57 is concerning due to the proven abbreviated scale applied. Reliability performed through SPSS using deleted item analysis failed to increase reliability. The conditions of the sample work environment may be of consideration in the low reliability of this measure. The department consists of the lending division of a bank that had experienced two years of record loan production volume. The immense loan volume caused employees to work overtime and experience workloads that far exceeded normal business operations for an extended period of time. The effects of this work environment may have compromised the accuracy of the validated scale.

PUSE mean proved to be high at 4.56 with a standard deviation of .8 and reliability of .9. PUSE has a positive significant correlation with job satisfaction ($r = .28$, $p < .01$). PEOU is considerably lower with a mean of 2.79, standard deviation of .07 and alpha reliability of .86. PEOU has a significant negative relationship with job satisfaction ($r = -.17$, $p < .05$). Job stress has a mean of 3.86 with a standard deviation of .83 and alpha reliability of .82. Job stress has a significant negative relationship with job satisfaction ($r = -.32$, $p < .01$). The COVID perceived email change construct had a mean of 3.94, standard deviation of .97 with alpha reliability of .56. The scale is limited, and no further analysis changed the reliability. The positive relationship is not significant. Of the control variables, age has a significant negative correlation with job satisfaction ($r = -.19$, $p < .01$). The negative correlation of age and job satisfaction is contrary to most findings. The COVID induced reliance on technology may have caused the negative relationship since studies find older employees having less acceptability and ease of use than younger individuals. The abrupt dependence on technology may have caused this anomaly.

HYPOTHESIS 1 – PUSE has a positive effect on job satisfaction.

Hypothesis 1 states PUSE has a positive effect on job satisfaction. The hypothesis is supported. PUSE has a positive effect on job satisfaction (B=.22, p < .01), after controlling for job type (B=.03, p > .05), gender (B=-.12, p>.05), and age (B=-.01, p > .05), which are not related to job satisfaction. Overall, PUSE explains 11.4% of variance in job satisfaction (r^2 = .114) and overall model was significant (F(4,142) = 4.58, p <.01). The findings extend research, COVID may have strengthened the relationship due to the increase reliance on technology (Table 4, Model 2).

HYPOTHESIS 2 – PEOU has a positive effect on job satisfaction.

Hypothesis 2 states PEOU has a positive effect on job satisfaction. An employees' perceived ease of use did not have a significant relationship to job satisfaction. Employees did not have a choice in the new technology adaption which may have influenced the relationship. The hypothesis is not supported, regression results are not significant (B=-.06, p > .05). The overall model results are (F(4,142) = 2.90, p < .05). (Table 4, Model 3)

HYPOTHESIS 3 – perceived automated email reduction will have a moderating effect on the relationship between job stress and job satisfaction.

Studies have shown the relationship between job stress and job satisfaction to have a negative correlation. Singh and Dubey (2011) revealed stress is significantly negatively correlated to job satisfaction. Research has supported the inverse relationship between these constructs. Studies on email volume has found the relationship between email volume and stress. Barley et al. (2011) associated higher levels of stress with higher levels of email volume. The perception of higher email volume may moderate the relationship between stress and job satisfaction. The study did not find survey data to link the moderating effect of lower perceived email. The hypothesis is not supported, regression results are not significant, change in (F(1,140) = .67, p > .05). Due to the COVID environment, additional constructs not considered could have a moderating effect. The changing work environment may produce new variables to the job that effect the relationship between job stress and job satisfaction (Table 5).

Table 7

Model 1	β	Standard Error	*t*
Constant	4.41**	0.05	99.00
JOB	0.03	.02	1.24
M-F	-0.16	.09	-1.65
AGE	-.01*	.00	-2.44
N= 147		F(3,143) = 3.125, p < .05	
* *p* < .05**			
p < .01	R^2 =	0.06	

Table 8

Model 1	β	Standard Error	*t*
Constant	4.41**	0.04	105.42
JOB	0.03*	0.02	1.16
M-F	-0.20	0.09	-2.20
AGE	-0.01	0.00	-1.88
COVID center	0.1*	0.04	2.31
Stress center	0.29**	0.07	4.24
N= 147		F(5,141) = 6.35, p < .01	
* *p* < .05	R^2 =	0.12	
** *p* < .01		*Change in R^2 = .12*	
		Change in F(2,141) = 10.55, p < .01	

Table 9

Model 3	β	Standard Error	*t*
Constant	4.41**	0.04	104.82
JOB	0.03	0.02	1.11
M-F	-0.21*	0.09	-2.29
AGE	-0.01	0.00	-1.88
COVID center	0.1*	0.05	2.22
Stress center	0.29**	0.07	4.26
COVID Stress Int	0.05	0.06	0.82
N= 147		F(6,140) = 5.39, p < .01	
* *p* < .05	R^2 =	0.14	
** *p* < .01		*Change in R^2 = .004*	
		Change in F(1,140) = 4.47, p > .05	

HYPOTHESIS 4 - perceived automated email reduction will have a moderating effect on the relationship between PUSE and job satisfaction.

This hypothesis is supported. The interaction of lower perceived email was significant after controlling for job type, gender, and age. The sample with lower perceived email has a more strongly positive relationship between PUSE and job satisfaction (gradient of the slope = .3, p < .01) than those with higher perceived email (gradient of slope = -.12, p > .05). Employees with lower expectations of perceived email volume moderated the relationship between PUSE and job satisfaction. An employee who has a positive opinion on the usefulness to complete their job may also see benefit from lower email volume (Figure 1). Employees with high perception of email may not cause any relationship change in the usefulness of technology since the level of email volume does not affect their opinion of the usefulness of technology. Overall, the model including the IV, moderator and control variable, explains significant variance in job satisfaction (F(6,140) = 4.26, p < .01; r^2 = .15). Further, the model that isolated the interaction term explained 2.7% of unique variance in job satisfaction (change in r^2 =.027, change in F(1,140) = 4.47, p < .05). The amount of variance of 2.7% is positive but relatively small percentage of variance (Table 6).

Table 10

Model 1	β	Standard Error	*t*
Constant	4.41**	0.05	99.00
JOB	0.03	.02	1.32
M-F	-0.16	.09	-1.89
AGE	-.01*	.00	-1.29
N= 147		F(3,143) = 3.125, p < .05	
* *p* < .05	R^2 =	0.06	
** *p* < .01			

Table 11

Model 2	β	Standard Error	*t*
Constant	4.41**	0.04	101.90
JOB	0.03	0.02	1.52
M-F	-0.14	0.09	-1.41
AGE	-0.01	0.00	-1.43
COVID center	0.07	0.05	1.44
PUSE center	0.21**	0.08	2.78
N= 147		F(5,141) = 4.11, p < .01	
* *p* < .05	R^2 =	0.13	
** *p* < .01		*Change in R^2 = .07*	
		Change in F(2,141) = 5.31, p < .01	

Table 12

Model 3	β	Standard Error	*t*
Constant	4.41**	0.04	102.73
JOB	0.03	0.02	1.34
M-F	-0.12	0.09	1.27
AGE	-0.01	0.00	-1.91
COVID center	0.07	0.05	1.49
PUSE center	0.09	0.09	0.911
COVID PUSE Int	-0.15*	0.07	-2.12
N= 147		F(6,140) = 4.26, p < .01	
* *p* < .05	R^2 =	0.15	
** *p* < .01		*Change in R^2 = .027*	
		Change in F(1,140) = 4.47, p < .05	

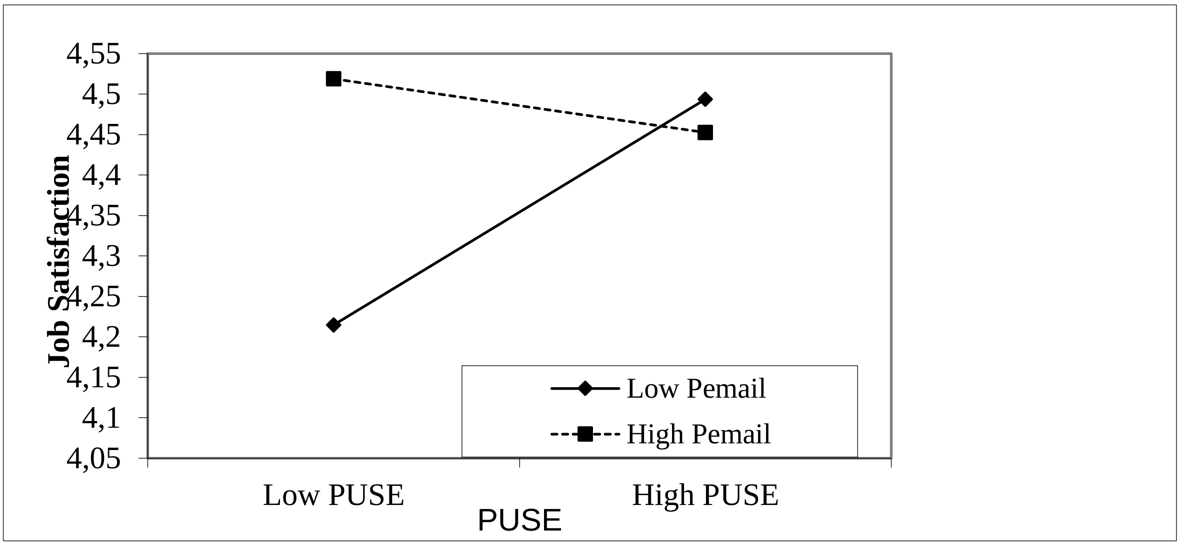

Figure 1. PUSE moderation of Job Satisfaction

HYPOTHESIS 5 – perceived automated email reduction will have a moderating effect on the relationship between PEOU and job satisfaction.

PEOU measures the degree an employee's use of technology will be free of effort. The combination of the new technology with increased use of existing tools, primarily email, may moderate the relationship between PEOU and job satisfaction. The findings did not prove to be highly correlated. The hypothesis is not supported, regression results are not significant ($F(1,140) = .09$, $p > .05$). COVID forced an immediate technological immersion for job communications. Usage of new technology was immediate, with little to no training. Employees must use these new mediums without prior knowledge and training which may have affected the results. (Table 7).

Table 13

Model 1	β	Standard Error	*t*
Constant	4.41**	0.05	99.00
JOB	0.03	.02	1.24
M-F	-0.16	.09	-1.65
AGE	-.01*	.00	-2.44
N= 147		F(3,143) = 3.125, p < .05	
* *p* < .05	R^2 =	0.06	
** *p* < .01			

Table 14

Model 2	β	Standard Error	*t*
Constant	4.41**	0.04	100.06
JOB	0.03	0.02	1.28
M-F	-0.16	0.09	-1.60
AGE	-0.01	0.00	-1.87
COVID center	0.08	0.04	1.7
PEOU center	-.06	0.04	-1.51
N= 147		F(5,141) = 2.93, p < .05	
* *p* < .05	R^2 =	0.09	
** *p* < .01		*Change in R^2 = .033*	
		Change in F(2,141) = 2.54, p > .05	

Table 15

Model 3	β	Standard Error	*t*
Constant	4.41**	0.04	99.74
JOB	0.03	0.02	1.26
M-F	-0.21	0.09	-1.61
AGE	-0.01	0.00	-1.83
COVID center	0.1	0.05	1.68
PEOU center	0.29	0.07	-1.52
COVID PEOU Int	0.05	0.06	-0.3
N= 147		F(6,140) = 2.44, p < .05	
* *p* < .05	R^2 =	0.1	
** *p* < .01		*Change in R^2 = .001*	

ACADEMIC AND PRACTICAL IMPLICATIONS

Significant relationships between several constructs add to the research literature. Most notably, the strong negative relationship between stress and job satisfaction. The additional stress that may result from changes brought about by COVID may have increased this relationship ($B = -.27$, $p < .001$). Although some stress is needed for job performance, excessive stress results in a strong negative correlation with job satisfaction. The study found stress attributed to 15% variance in job satisfaction. Opportunities to reduce stress can have a profound positive effect on job satisfaction. Because of its impact on important organizational outcomes, the management of workplace stress has become a management imperative (Zeffane & McLoughlin, 2006). Locating stressors and finding techniques in which to reduce employee stress continues to be a high priority in any organization. Assessing methods to aid in the reduction may constitute substantial resources to accommodate implementation.

Findings from business surveys suggest that email traffic is consuming a proportion of the working day which has been associated with over-monitoring, workflow disruption, work-life conflict and addiction to email – all which in turn are associated with higher levels of work-related stress (Pignata, Lushington, Sloan & Buchanan, 2015; Barley, Meyerson & Grodal, 2011; Cooper, 2005; Dabbish & Kraut, 2006; Hair, Renaud & Ramsay, 2007; Hill, Hawkins, Ferris & Weitzman, 2001). A 2011 study by Barley, Meyerson and Grodel found employees blamed email as a source of stress in their job, causing them to work longer hours. We should question, review, and examine the optimal use of email to minimize individual stress and increase job satisfaction encouraging maximize employee performance, thus creating plausible competitive advantages for businesses and universities. The introduction of COVID into our lives has increased the necessity for communication methods beyond face-to-face interactional collaboration. Prior to COVID, the utilization of videoconference discussions primarily occurred in instances where face to face was difficult or expensive to accommodate, such as cross-continent corporate meetings. During COVID, these videoconference channels have become the common communication preference between individuals that had previously met in a close personal office setting. COVID entrenched all employees into technology usage for many job duties that were previously performed without technology.

PUSE is the perception of an individual that use of technology will improve job performance. PUSE has a strong positive relationship with job satisfaction ($B = .17$, $p < .05$). In the sample, PUSE explains 11% of the variance in job satisfaction providing additional support of the importance of user perception of acceptability in technology use and its contribution to job satisfaction. Perception of email volume further moderated the effect of PUSE on job satisfaction. Employees with lower perceived email volume have a more strongly positive relationship between PUSE and job satisfaction as opposed to those with higher perceived email volume. The model that isolated the interaction term explained 2.7% of unique variance in job satisfaction by perceived email volume.

A significant relationship between PEOU and job satisfaction was not found in the research. Although the relationship between stress and job performance has a significant negative relationship, reduction of email's moderating effect between the relationship is not significant. Strategies aimed at simply reducing email volume and changing individual behaviors may not be enough (Sumecki et al., 2011). Several factors may have contributed to the insignificant effect. The number of employees that perceived an email reduction was 13.6% of the sample even though they were aware of the reduction program. The majority of respondents felt email volume continued to increase during the reduction program with 54% answering the survey with a perceived increase in email volume. The increase in technology use in the remote work environment may have muted the effect of the automated email reduction program.

As society transitions through post COVID protocols, many individuals may continue to work remotely instead of returning to the office. A change in the acceptability of working out of the office is developing as individuals prove they can be effective and efficient without traveling to an office. Independent conversations that commonly occurred during daily interaction between individuals located in an office setting has been commonly replaced by electronic means. Teleconference mediums such as Zoom, Face time and Microsoft instant messaging systems produce additional outlets for communication, but email is still relied on to communicate essential individual and group information. We must continue to explore our electronic communications methods, systems, and procedures. The need for proper use and efficient consistent processes should be evaluated, measured, and developed to convalesce our electronic communication mediums.

DISCUSSION

Some limitations on the generalization of the data and its findings due to the small sample size from a bank lending department may be an external validity concern. The measurement of perceived email volume may not fully capture the effectiveness of the reduction program since the direct link between email volume and individual data was not captured for analysis. The pairing of an email reduction program within the COVID time period provides additional challenges due to the fact that the use of technology was increasing during the email reduction program. The changing conditions provoked during COVID may create additional constructs not considered. Email use may have been increasing at the lessor degree due to the reduction protocol, but the perception may not be realized due to a plausible overall increase in email volume. Correlation of actual volume to individual sample data may provide improved relationship analysis. Reliability coefficient for job satisfaction of .57 is less than desired and may be explained by the job characteristics of the sample, the sample ranged from task-oriented employees to high stress commissioned employees. The sample consisted of employees who work in the lending that had experienced two years of record loan production volume. The immense loan volume created workloads that far exceeded normal business operations. Overtime work hours and increased responsibilities for an extended period of time may have affected the survey results.

The volume reduction of email was reduced and encouraging, but an intriguing result provoked the discussion on beyond the effectiveness and need for email but if the individual actually needed the information email provided or whether they perceived the need but the data could be attained in a more efficient format, such as summary reports of data derived from a large grouping of email verses a large quantity of individual data points. Several managers insisted on receiving automated emails even though the information could be effectively reported and evaluated through a report. That report contained a precise and encompassing valuation of the data thus the need for the constant email notification would be eliminated. The individual manager felt they needed the notification even though very few of the emails were read and the distraction and time component ignored. The constant need for this stimulus may be more pronounced within different samples and in some cases the individual may prefer the barrage of emails but may prove that limiting these and using summary reports for optimization of their job responsibilities.

Further studies using data for direct analysis pre-test, stimulus, then post-test may prove more reliable and significant. Recommend future research with larger sample size in other industries for generalization of the model. Research should also consider additional email electronic communication means and programs supplementing some of the responsibilities that formerly utilized face to face communication exchanges. The challenge on email reduction begins with the realization that its use may be excessive and hindering or decreasing productivity. 71% (104) of survey respondents perceived email volume to increase post COVID. Email volume and its effect on productivity is subject area in which management may need to provide greater attention.

The sample of bank employees provides an excellent environment rich with email use spanning from common communication to regulatory compliance use. The reduction program utilized was unique in format and analysis procedure in the reduction processes and email necessity criteria but applicable in theory to problematic issues of email and electronic media overload creating inefficiencies, distraction, and stress. Future studies identifying a formal and consistent adherence to email policy enacted through automation and individual use will further strengthen applicable approaches and studies necessary for implementation of effective email reduction and effective use.

CONCLUSIONS

The objective of this study is to examine the relationship between job satisfaction, stress, PUSE, PEOU utilizing formalized email reduction process and perceived automated email volume. The sample consisted of 147 employees in a bank lending department who were employed during the 12-month email reduction program. The survey questions originated from prior validated surveys. The data was analysed with mean, standard deviation, correlation, regression, and ANOVA tests. Stress was found to have a negative effect on job satisfaction, contributing to 15% variance in our sample. PUSE had a positive effect on job satisfaction, accounting for 11.4% of the variance job satisfaction. Reduction of email had a significant moderating effect on PUSE, accounting for 2.7% variance in our sample.

The result’s further research findings. The increased use of technology in our communication and the importance of our attitude toward technology in conjunction with understanding and controlling usage is imperative. COVID has changed the workforce through the transition from an office-based environment to a remote, home-based work environment. Many employees did not return to the office and continue work from remote locations with no intention of returning to office life. The higher levels of remote work may continue to pressure employee’s use of electronic mediums. Further complications arise with the combination and integration of remote based mediums simultaneously in conjuncture with office based. Now, meetings and conferences often combine remote and office-based employees, creating new experiences and challenges in understanding how to effectively communicate. COVID has enacted a new reliance on technology and its acceptance in our changing work behaviours creating robust new challenges and stressors correlating to job satisfaction. This study's findings help us understand all these important relationships based on the empirical study in the field setting.

REFERENCES

Adi Permana, I. B. G., & Setianto, D. P. (2019). The Impact of Task Technology Fit, System Quality and Information Quality to User Performance: Perceived Ease Usefullness and Perceived Ease of Use as Mediation. *International Journal of Organizational Innovation*, *12*(2), 335–340.

Ahmad, A., & Afgan, S. (2016). The Relationship of Job Stress and Turnover Intention in Commercial Banks of Pakistan by Assessing the Mediating Role of Burnout. *Journal of Business Strategies; Karachi*, *10*(1), 1–23.

Ahmed, R. R., Warraich, U. A., Khoso, I., & Ahmad, N. (2014). Impact of Stress on Job Performance: An Empirical study of the Employees of Private Sector Universities of Karachi. *Global Management Journal for Academic & Corporate Studies; Karachi*, *4*(2), 104–108.

Anand, S., Vidyarthi, P., Singh, S., & Ryu, S. (2015). Family interference and employee dissatisfaction: Do agreeable employees better cope with stress? *Human Relations*, *68*(5), 691–708. https://doi.org/10.1177/0018726714539714

Antoniou, A.-S. G., Davidson, M. J., & Cooper, C. L. (2003). Occupational stress, job satisfaction and health state in male and female junior hospital doctors in Greece. *Journal of Managerial Psychology; Bradford*, *18*(6), 592–621. http://dx.doi.org.ezproxy.depaul.edu/10.1108/02683940310494403

Barley, S. R., Meyerson, D. E., & Grodal, S. (2011). E-mail as a Source and Symbol of Stress. *Organization Science*, *22*(4), 887–906.

Bellotti, V., Ducheneaut, N., Howard, M., Smith, I., & Grinter, R. E. (2005). Quality Versus Quantity: E-Mail-Centric Task Management and Its Relation With Overload. *Human-Computer Interaction*, *20*(1/2), 89–138. https://doi.org/10.1207/s15327051hci2001&2_4

Borg, M. G., & Riding, R. J. (1991). Occupational stress and satisfaction in teaching. *British educational research journal*, *17*(3), 263-281.

Bresciani, S., & Eppler, M. (2015). *Extending Tam to Information Visualization: A Framework for Evaluation*. *18*(1), 14.

Burgess, A., Jackson, T., & Edwards, J. (2005). Email training significantly reduces email defects. *International Journal of Information Management*, *25*(1), 71–83. https://doi.org/10.1016/j.ijinfomgt.2004.10.004

Camargo, M. R. (2008). A Grounded Theory Study of the Relationship between E-Mail and Burnout. *Information Research: An International Electronic Journal*, *13*(4), 15.

Cohen, S. and Williamson, G. (1988), "Perceived stress in a probability sample of the USA", in Spacapan, S. and Oskamp, S. (Eds), The Social Psychology of Health, Sage, Newbury Park, California, CA, pp. 31-68.

Davis, F. D. (1986). *A Technology Acceptance Model for Testing New End-User Information Systems: Theory and Results.* [Ph.D., Massachusetts Institute of Technology]. http://search.proquest.com/docview/303543930/4A1ADC9F96654489PQ/4

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Davis, F. D., & Venkatesh, V. (1996). A critical assessment of potential measurement biases in the technology acceptance model: Three experiments. *International Journal of Human-Computer Studies*, *45*(1), 19–45. https://doi.org/10.1006/ijhc.1996.0040

Detienne, K. B., Agle, B. R., Phillips, J. C., & Ingerson, M. (2012). The Impact of Moral Stress Compared to Other Stressors on Employee Fatigue, Job Satisfaction, and Turnover: An Empirical Investigation. *Journal of Business Ethics: JBE; Dordrecht*, *110*(3), 377–391. http://dx.doi.org.ezproxy.depaul.edu/10.1007/s10551-011-1197-y

Diab-Bahman, R., Link to external site, this link will open in a new window, & Al-Enzi, A. (2020). The impact of COVID-19 pandemic on conventional work settings. *The International Journal of Sociology and Social Policy*, *40*(9/10), 909–927. https://doi-org.ezproxy.depaul.edu/10.1108/IJSSP-07-2020-0262

E, K. K., Barling, J., & Shah, A. (1993). Industrial relations stress and job satisfaction: Concurrent effects and mediation: Summary. *Journal of Organizational Behavior (1986-1998)*, *14*(5), 447.

Fried, Y., Shirom, A., Gilboa, S., & Cooper, C. L. (2008). The mediating effects of job satisfaction and propensity to leave on role stress-job performance relationships: Combining meta-analysis and structural equation modeling. *International Journal of Stress Management*, *15*(4), 305–328. https://doi.org/10.1037/a0013932

Gupta, A., Sharda, R., & Greve, R. A. (2011). You’ve got email! Does it really matter to process emails now or later? *Information Systems Frontiers; New York*, *13*(5), 637–653. http://dx.doi.org.ezproxy.depaul.edu/10.1007/s10796-010-9242-4

Hackman, J. R., Oldham, G. R., Hackman, J. R., & Oldham, G. R. (1975). Job Diagnostic Survey. *Development of the Job Diagnostic Survey*, *60*(2), 159–170.

Hassan, M., Azmat, U., Sarwar, S., Adil, I. H., & Gillani, S. H. M. (2020). Impact of Job Satisfaction, Job Stress and Motivation on Job Performance: A Case from Private Universities of Karachi. *Kuwait Chapter of the Arabian Journal of Business and Management Review*, *9*(2), 31–41.

Huang, E. Y., & Lin, S. W. (2009). Do Knowledge Workers Use E-Mail Wisely? *The Journal of Computer Information Systems; Stillwater*, *50*(1), 65–73.

Huang, E. Y., Lin, S. W., & Lin, S.-C. (2011). A quasi-experiment approach to study the effect of e-mail management training. *Computers in Human Behavior*, *27*(1), 522–531. https://doi.org/10.1016/j.chb.2010.09.021

Hwang, Y. (2005). Investigating enterprise systems adoption: Uncertainty avoidance, intrinsic motivation, and the technology acceptance model. *European Journal of Information Systems*, *14*(2), 150–161. http://dx.doi.org.ezproxy.depaul.edu/10.1057/palgrave.ejis.3000532

Hwang, Y., (2008). A preliminary examination of the factors for knowledge sharing in technology mediated learning, *Journal of Information Systems Education*, 19(4), 419. https://jise.org/volume19/n4/JISEv19n4p419.html

Hwang, Y. (2011). Predicting Attitudes Toward Knowledge Sharing by E-Mail: An Empirical Study. *International Journal of Human-Computer Interaction*, *27*(12), 1161–1176. https://doi.org/10.1080/10447318.2011.565706

Hwang, Y. (2016). Understanding social influence theory and personal goals in e-learning. *Information Development*, 32(3), 466-477. https://journals.sagepub.com/doi/abs/10.1177/0266666914556688

Hwang, Y., Kettinger, W. J., & Yi, M. Y. (2013). A study on the motivational aspects of information management practice, *International Journal of Information Management*, 33(1), 177-184. https://www.sciencedirect.com/science/article/abs/pii/S0268401212001193

Hwang, Y., Kettinger, W. J., & Yi, M. Y. (2015). Personal information management effectiveness of knowledge workers: Conceptual development and empirical validation. *European Journal of Information Systems*, *24*(6), 588–606. https://doi.org/10.1057/ejis.2014.24

Jackson, A. T., & Frame, M. C. (2018). Stress, health, and job performance: What do we know? *Journal of Applied Biobehavioral Research*, *23*(4), 1–14. https://doi.org/10.1111/jabr.12147

Jackson, T., Dawson, R., & Wilson, D. (2003a). Reducing the effect of email interruptions on employees. *International Journal of Information Management*, *23*(1), 55–65. https://doi.org/10.1016/S0268-4012(02)00068-3

Jackson, T., Dawson, R., & Wilson, D. (2003b). Reducing the effect of email interruptions on employees. *International Journal of Information Management*, *23*(1), 55–65. https://doi.org/10.1016/S0268-4012(02)00068-3

Jackson, T. W., Burgess, A., & Edwards, J. (2006). A simple approach to improving email communication. *Association for Computing Machinery. Communications of the ACM; New York*, *49*(6), 107–109. http://dx.doi.org.ezproxy.depaul.edu/10.1145/1132469.1132493

Jackson, T. W., Dawson, R., & Wilson, D. (2003). Understanding Email Interaction Increases Organizational Productivity. *Communications of the ACM*, *46*(8), 80–84. https://doi.org/10.1145/859670.859673

Jackson, T. W., & Lichtenstein, S. (2011). Optimising e-mail communication: The impact of seminar- and computer-based training. *International Journal of Internet and Enterprise Management; Olney*, *7*(2), 197.

Jamal, M. (1997). Job stress, satisfaction, and mental health: An empirical examination of self-employed and non-self-employed Canadians. *Journal of Small Business Management; Milwaukee*, *35*(4), 48–57.

Jermsittiparsert, K., Petchchedchoo, P., Kumsuprom, S., & Panmanee, P. (2021). THE IMPACT OF THE WORKLOAD ON THE JOB SATISFACTION: DOES THE JOB STRESS MATTER? *Academy of Strategic Management Journal, 20*, 1-13. https://ezproxy.depaul.edu/login?url=https://www-proquest-com.ezproxy.depaul.edu/scholarly-journals/impact-workload-on-job-satisfaction-does-stress/docview/2568313264/se-2?accountid=10477

Jerejian, A. C. M., Reid, C., & Rees, C. S. (2013). The contribution of email volume, email management strategies and propensity to worry in predicting email stress among academics. *Computers in Human Behavior*, *29*(3), 991–996. https://doi.org/10.1016/j.chb.2012.12.037

Johnson, S., Cooper, C., Cartwright, S., Donald, I., & al, et. (2005). The experience of work-related stress across occupations. *Journal of Managerial Psychology; Bradford*, *20*(1/2), 178–187. http://dx.doi.org.ezproxy.depaul.edu/10.1108/02683940510579803

Judge, T. A., Thoresen, C. J., Bono, J. E., & Patton, G. K. (2001). The job satisfaction–job performance relationship: A qualitative and quantitative review. *Psychological Bulletin*, *127*(3), 376–407. https://doi.org/10.1037/0033-2909.127.3.376

Kashif, M., Braganca, E., Awang, Z., & Cyril De Run, E. (2017). You abuse but I will stay: The combined effects of job stress, customer abuse, and emotional intelligence on employee turnover. *The Journal of Management Development; Bradford*, *36*(7), 899–914. http://dx.doi.org.ezproxy.depaul.edu/10.1108/JMD-06-2016-0095

Ko, E.-J., Kim, A.-H., & Kim, S.-S. (2021). Toward the understanding of the appropriation of ICT-based Smart-work and its impact on performance in organizations. *Technological Forecasting and Social Change*, *171*, 120994. https://doi.org/10.1016/j.techfore.2021.120994

Kohler, M. (2010). *Exploring the Relationships among Work-Related Stress, Quality of Life, Job Satisfaction, and Anticipated Turnover on Nursing Units with Clinical Nurse Leaders* [Ph.D., University of South Florida]. http://search.proquest.com/docview/823697942/abstract/961B227DC24A4EDCPQ/1

Lambert, E. G., Qureshi, H., Frank, J., Klahm, C., & Smith, B. (2018). Job Stress, Job Involvement, Job Satisfaction, and Organizational Commitment and Their Associations with Job Burnout Among Indian Police Officers: A Research Note. *Journal of Police and Criminal Psychology*, *33*(2), 85–99. http://dx.doi.org.ezproxy.depaul.edu/10.1007/s11896-017-9236-y

Mariani, M. G., Curcuruto, M., & Gaetani, I. (2013). Training opportunities, technology acceptance and job satisfaction: A study of Italian organizations. *Journal of Workplace Learning*, *25*(7), 455–475. https://doi-org.ezproxy.depaul.edu/10.1108/JWL-12-2011-0071

Marulanda-Carter, L., & Jackson, T. W. (2012). Effects of E-Mail Addiction and Interruptions on Employees. *Journal of Systems and Information Technology*, *14*(1), 82–94.

Masihabadi, A., Rajaei, A., Koloukhi, A. S., & Parsian, H. (2015). Effects of stress on auditors' organizational commitment, job satisfaction, and job performance. *International Journal of Organizational Leadership*, *4*(3), 303–314. http://dx.doi.org.ezproxy.depaul.edu/10.19236/IJOL.2015.03.07

Mazzola, J. J., & Disselhorst, R. (2019). Should we be "challenging" employees?: A critical review and meta-analysis of the challenge-hindrance model of stress. *Journal of Organizational Behavior*, *40*(8), 949–961. https://doi.org/10.1002/job.2412

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information systems research*, *2*(3), 192-222.

Morris, M. G., & Venkatesh, V. (2000). Age differences in technology adoption decisions: Implications for a changing work force. *Personnel Psychology; Durham*, *53*(2), 375–403.

Nixon, A. E., Mazzola, J. J., Bauer, J., Krueger, J. R., & Spector, P. E. (2011). Can work make you sick? A meta-analysis of the relationships between job stressors and physical symptoms. *Work & Stress*, *25*(1), 1–22. https://doi.org/10.1080/02678373.2011.569175

Nowak, K., Kuzminska, A. O., & Kowalczyk, K. K. (2018). The Effect of Overflow at Workplace on Employees Productivity and Well Being. *Economic and Social Development: Book of Proceedings; Varazdin*, 322–331. http://search.proquest.com/abicomplete/docview/2131160596/abstract/E12661E72CDB4B4CPQ/141

O'Kane, P., Palmer, M., & Hargie, O. (2007). Workplace interactions and the polymorphic role of e-mail. *Leadership & Organization Development Journal; Bradford*, *28*(4), 308–324. http://dx.doi.org.ezproxy.depaul.edu/10.1108/01437730710752193

Okolo, D., Kamarudin, S., & Ahmad, U. N. (2018). An Exploration of the Relationship between Technostress, Employee Engagement and Job Design from the Nigerian Banking Employee's Perspective. *Management Dynamics in the Knowledge Economy; Bucharest*, *6*(4), 511–530. http://dx.doi.org.ezproxy.depaul.edu/10.25019/MDKE/6.4.01

Pignata, S., Lushington, K., Sloan, J., & Buchanan, F. (2015). Employees' perceptions of email communication, volume and management strategies in an Australian university. *Journal of Higher Education Policy & Management*, *37*(2), 159–171. https://doi.org/10.1080/1360080X.2015.1019121

Pillet, J.-C., & Carillo, K. D. A. (2016). Email-free collaboration: An exploratory study on the formation of new work habits among knowledge workers. *International Journal of Information Management*, *36*(1), 113–125. https://doi.org/10.1016/j.ijinfomgt.2015.11.001

Radicati Group (2007), Addressing Information Overload in Corporate E-mail: the Economics of User Attention, White Paper, April, available at: www.radicati.co

Ramsay, J., & Renaud, K. (2012). Using insights from email users to inform organisational email management policy. *Behaviour & Information Technology*, *31*(6), 587–603. https://doi.org/10.1080/0144929X.2010.517271

Rekha, B., & Paramanandam, P. (2017). Job Stress and Job Satisfaction Among the Managerial Personnel of Textile Industry. *Sumedha Journal of Management; Hyderabad*, *6*(3), 65–74.

Ridzuan, A. A., Zainol, N. A. M., Liaw, J. O. H., Yaacob, S., & Ismail, A. (2017). The Effects of Stress Factor on Job Performance. *Journal of Economic & Management Perspectives; Mersin*, *11*(4), 1235–1243.

Roberti, J. W., Harrington, L. N., & Storch, E. A. (2006). Further Psychometric Support for the 10-Item Version of the Perceived Stress Scale. *Journal of College Counseling; Alexandria*, *9*(2), 135–147.

Robertson, I. T., Baron, H., Gibbons, P., MacIver, R., & Nyfield, G. (2000). Conscientiousness and managerial performance. *Journal of Occupational and Organizational Psychology*, *73*, 171–180.

Rosen, C. C., Simon, L. S., Gajendran, R. S., Johnson, R. E., Lee, H. W., & Lin, S.-H. (Joanna). (2019). Boxed in by your inbox: Implications of daily e-mail demands for managers' leadership behaviors. *Journal of Applied Psychology*, *104*(1), 19–33. https://doi.org/10.1037/apl0000343

Schuldt, B. A., & Totten, J. W. (2008). Technological Factors & Business Faculty Stress. *Allied Academies International Conference. Academy of Information and Management Sciences. Proceedings; Arden*, *12*(1), 13–18.

Siders, M. A., George, G., & Dharwadkar, R. (2001). The Relationship of Internal and External Commitment Foci to Objective Job Performance Measures. *Academy of Management Journal*, *44*(3), 570–579. https://doi.org/10.5465/3069371

Singh, A. P., & Kumar, Dubey, A. (2011). Role of Stress and Locus of Control in Job Satisfaction Among Middle Managers. *IUP Journal of Organizational Behavior*, *10*(1).

Skalli, A., Theodossiou, I., & Vasileiou, E. (2008). Jobs as Lancaster goods: Facets of job satisfaction and overall job satisfaction. *The Journal of Socio-Economics*, *37*(5), 1906–1920. https://doi.org/10.1016/j.socec.2008.04.003

Springer, G. J. (2011). A Study of Job Motivation, Satisfaction, and Performance among Bank Employees. *Journal of Global Business Issues*, *5*(1), 29–42.

Sullivan, S., Bhagat, R. (1992). Organizational Stress, Job Satisfaction and Job Performance: Where Do We Go From Here? *Journal of Management,* 18(2), 353-374.

Sumecki, D., Chipulu, M., & Ojiako, U. (2011). Email overload: Exploring the moderating role of the perception of email as a 'business critical' tool. *International Journal of Information Management*, *31*(5), 407–414. https://doi.org/10.1016/j.ijinfomgt.2010.12.008

Tassabehji, R., & Vakola, M. (2005). Business Email: The Killer Impact. *Communications of the ACM*, *48*(11), 64–70. https://doi.org/10.1145/1096000.1096006

Varvogli, L., & Darviri, C. (2011). Stress Management Techniques: Evidence-based procedures that reduce stress and promote health. *Health Science Journal; Egaleo*, *5*(2), 74–89.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Vidgen, R., Sims, J., & Powell, P. (2011). Understanding e-mail overload. *Journal of Communication Management; London*, *15*(1), 84–98. http://dx.doi.org.ezproxy.depaul.edu/10.1108/13632541111105277

Yi, M. Y., & Hwang, Y. (2003). Predicting the use of web-based information systems: Self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model. *International Journal of Human-Computer Studies*, *59*(4), 431–449. https://doi.org/10.1016/S1071-5819(03)00114-9

Zeffane, R., & McLoughlin, D. (2006). Cooperation and stress: Exploring the differential impact of job satisfaction, communication and culture. *Management research news*.

Authors' Note

All correspondence should be addressed to
Yujong Hwang
DePaul University
USA
yhwang1@depaul.edu
ORCID 0000-0001-7323-6127

Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 20(1), May 2024, 70-92

FACTORS INFLUENCING FARMER ADOPTION OF CLIMATE-SMART AGRICULTURE TECHNOLOGIES: EVIDENCE FROM MALAYSIA

Mohd Amar Aziz
Faculty of Administrative Science and Policy Studies
Universiti Teknologi MARA Pahang
Malaysia

Noor Hadzlida Ayob
Faculty of Human Sciences
Universiti Pendidikan Sultan Idris
Malaysia

Nor Azira Ayob
Faculty of Administrative Science and Policy Studies
Universiti Teknologi MARA Negeri Sembilan
Malaysia

Yarina Ahmad
Institute for Biodiversity and Sustainable Development
Universiti Teknologi MARA Shah Alam
Malaysia

Kamaruddin Abdulsomad
School of Economics and Management
Department of Economic History
Lund University
Sweden

Abstract: *As technology advances, people become increasingly dependent on technological tools to increase their work efficiency and productivity. Farming methods in the agriculture sector are also undergoing a shift from conventional to technology-driven modern agriculture practices, primarily because of their benefits and potential to mitigate the effects of climate change. However, the adoption rate of climate-smart agriculture technologies (CSAT) is considered to be very slow. Thus, this study was conducted to examine the factors that lead farmers to adopt CSAT in their agricultural practices. A sample of 185 farmers was used to investigate the main influencing factors in four contexts. The developed model was analyzed using the partial least squares structural equation modeling method. The results of this study suggest that institutions play a critical role as a contextual factor that leads individuals and societies to engage with CSAT, builds confidence, and convinces farmers to adopt these technologies.*

Keywords: *climate smart agriculture technologies, institutions, environment, sustainability*

DOI: https://doi.org/10.14254/1795-6889.2024.20-1.4

INTRODUCTION

Given the current environmental crisis, climate-smart agriculture technologies (CSAT) are widely advocated as a means of ensuring the sustainability of food production. Despite serious global concerns about environmental issues and climate change, scaling up CSAT practices seems to be a challenge, especially in developing countries (Mazhar et al., 2021). Numerous forms and categories of CSAT exist, encompassing a wide array of technologies relevant to various aspects of farming. These include techniques for technical and practical agriculture, water and soil management, livestock care, as well as an assortment of technological tools and digital solutions, extending to renewable energy and emission reduction strategies. Within each of these categories, a diverse range of technological methods is available for implementation. Examples include diversified and rotational cropping systems, drip irrigation and rainwater harvesting systems, organic farming practices, the use of GPS, drones, and IoT sensors, agroforestry, and integration of solar and wind energy systems in agriculture. Farmers can adopt any of these methods as part of their efforts to mitigate climate change.

However, CSAT adoption is also associated with several risks and uncertainties, as well as potential financial costs that may influence farmers' decisions. Several factors, including institutional structure (Fusco et al., 2020; Mazhar et al., 2021; Totin, et al., 2018), farmer skill levels (Anuga et al., 2019; Lee, 2017; Morgan et al., 2018), increasing workload (Andrieu et al., 2017; Tsige, Synnevåg, & Aune, 2020), need for new skills (Raj & Garlapati, 2020; Shahbaz, 2022), lack of awareness, lack of information, lack of experience (Mashi, Inkami, & Oghenejabor, 2022; Nyasimi et al, 2017; Ouédraogo et al., 2019), and perceptions of new technologies (Khoza et al., 2021; Ouédraogo et al., 2019; Senyolo et al., 2018) are considered barriers to farmer adoption and use of CSAT.

According to Raile et al. (2021) and Makate (2019), when attempting to encourage the adoption of CSAT, it is also important to consider factors that create or discourage incentives. Incentives, such as financial and non-financial benefits, can encourage farmers to adopt new technologies, while disincentives, such as the cost of a new technology, can discourage farmers from adopting it. Financial disincentives often arise when new technologies require expensive investments, such as the purchase of land or equipment, which may not be feasible for smallholder farmers (Autio, Johansson, Motaroki, Minoia, & Pellikka, 2021). Non-financial disincentives may also arise if the CSAT is not compatible with traditional farming practices, which may result in lower yields and higher input costs. For example, a CSAT that requires specialized equipment or different crop varieties may not be compatible with smallholders' existing farming practices (Akouwerabou, Zanré, Savadogo, & Kaboré, 2022). To counter this, information from farmers to technology providers is crucial to ensure that their products are more compatible with traditional farming practices. This can only be done through a concerted effort by many, including the government, to assist farmers adopt CSAT. It is important to encourage farmers to adopt CSAT because this agricultural innovation can help farmers with food security, climate change adaptation, and mitigation (Meshesha, Birhanu, & Ayele, 2022).

The literature also suggests that governments can provide financial and technical support to farmers, while non-governmental organizations can disseminate information about the benefits of CSAT and provide training to farmers (Dey & Mishra, 2022; Waaswa, Nkurumwa, Kibe, & Kipkemoi, 2022). Strategies include expanding the commercialization of the technology (Casey, Bisaro, Valverde, Martinez, & Rokitzki 2021). If the technology is not effectively commercialized, farmers may not even know it exists. In addition, trialability is one of the strategies that can be used to promote CSAT to farmers (Kabir et al., 2022). This will enable farmers to have a first-hand experience with the technology, which can help reduce some of their risk aversion. Farmer motivation is also an important factor influencing CSAT adoption. Farmers may be motivated to adopt CSAT if the technology is easy to use and the benefits are apparent (Antwi-Agyei et al., 2021). In addition, farmers are more likely to adopt CSAT if they see their peers using the technology (Khoza et al, 2021; Totin et al, 2018). This demonstrates that institutional, individual, and social context influences farmers' use of CSAT.

Although previous studies have explained the numerous factors that lead to the adoption of CSAT, there is a dearth of research that comprehensively frames the relationship between these aspects and the institutional, individual, and societal context. It is essential to examine the factors from a contextual perspective to determine which elements require attention and improvement to promote CSAT adoption among farmers. This is because many farmers are affected by climate change, resulting in disappointing agricultural outcomes. In 2021, Malaysian agriculture contributed 7.1 percent to the country's gross domestic product (GDP), with this figure declining slightly by 0.3 percent from the previous year (Statista Search Department, 2022). The country has experienced more extreme weather conditions, including more floods and landslides. Unpredictable weather and climate conditions, as well as a lack of technological solutions to support farmers, could affect agricultural production (Rahman, 2009). The initial strategy, which uses CSAT, is therefore considered suitable to solve the crisis. With this in mind, it is expected that this study will help policymakers determine which areas need to be emphasized and formulate ideas based on the data obtained to encourage farmers to adopt the technologies.

THE THEORETICAL UNDERPINNINGS

This study integrates several important theories that serve as the basis for analyzing the factors that influence farmers' adoption of CSAT in different contexts. The three integrated theories are the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology Acceptance Model (TAM), and the Diffusion of Innovation (DOI) theory. The factors for CSAT adoption are explained with reference to the three theories above, based on institutional, individual, and societal contexts, respectively.

The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh, Bala, and Davis in 2003. This theory attempts to explain how individuals and groups adopt and use technology. Four constructs serve as the basis for the theory: performance expectancy, effort expectancy, social influence, and facilitating conditions. This theory states that individuals and groups adopt and use technology to fulfill their performance and effort expectations. In addition, social influence and facilitating conditions play a role in an individual's decision to use or not use technology.

Venkatesh, Thong, and Xu (2012) extended the UTAUT model by adding hedonic motivation, price value, and habit as additional factors that influence a person's decision to adopt and use technology. Hedonic motivation is the extent to which a person derives pleasure from using technology. Price value is the degree to which a person believes the technology is worth the price they pay, and habit is a person's tendency to use technology out of habit rather than due to external factors (Venkatesh et al., 2012). However, in this study, two variables, hedonic motivation and habit, were omitted.

This is because climate-smart agriculture is not a fancy new technological device or tool for self-improvement, but rather a concern related to aspects of more effective agricultural management. Farmers are more interested in the benefits they derive from using technology. They will not use technology just for hedonistic purposes. They are primarily motivated by economic factors, such as increasing their productivity, reducing costs, and maximizing profits. If a technology does not offer economic benefits or does not align with farmers' financial goals, they are less likely to adopt it, even if it offers hedonistic benefits (Akouwerabou et al., 2022; Autio et al., 2021). For this reason, hedonic motivation and habit are not considered in the model, resulting in a more parsimonious model.

The Technology Acceptance Model (TAM)

The technology acceptance model (TAM) is a theoretical model used to explain and predict user acceptance of technology. The technology acceptance model consists of four main components: perceived ease of use, perceived usefulness, attitude toward use, and behavioral intention to use. Recently, UTAUT has replaced TAM in many usage-based research studies. Perceived usefulness and perceived ease of use can be related to effort and performance expectancies respectively and are two of the similar constructs (Dwivedi, Mustafee, Carter, & Williams, 2010; Sair & Danish, 2018).

Although perceived ease of use is considered very similar and comparable to effort expectancy, perceived usefulness is also considered similar to performance expectancy. However, in this research, the terminology of perceived ease of use and perceived usefulness preferred by TAM was used. It is assumed that the items for both constructs are closer to the individual perspective of technology adoption. Therefore, this study uses the terms 'perceived ease of use' and 'perceived usefulness' to measure an individual's role in technology use.

The Diffusion of Innovation (DOI)

The theory of diffusion of innovations (DOI) assumes that innovations are not static but are constantly evolving and growing over time. Specifically, innovations are most likely to be adopted by members of the same social group or class who are already using similar technologies. For an innovation to spread beyond its original group, it must first be accepted and adopted by the group that was originally most likely to adopt it. Relative advantage, compatibility, complexity, observability, and trialability are considered the five constructs underlying DOI theory (Scott et al., 2008).

However, various constructs were released to develop a model congruent with institutional, individual, and social contexts so that parsimony could be achieved. According to Alkhwaldi and Kamala (2017), a well-established and comprehensive theoretical model should consider parsimony in terms of simplifying the model with the fewest constructs and maximum predictive potential. Therefore, this study uses only the construct of trialability to integrate the model, which is included in an institutional framework for DOI. The relationship between constructs based on institutional, individual, and social contexts in technology adoption is explained in the next section, which also develops a study model.

RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

This study examines the institutional, individual, social, and environmental contexts that are hypothesized to be the most influential factors in CSAT adoption. These four contexts are derived from the previously discussed theories UTAUT, TAM, and DOI, and the constructs of the theory are assigned according to the suitability of the context.

Institutional Context

Several theoretical constructs can be considered as part of the institutional context. Commercialization is one of the antecedent constructs that does not appear in the theory discussed, but is considered appropriate to be placed in an institutional context. The commercialization of a technology can influence its perceived usefulness and ease of use. Kim, Park, Sawng, and Park (2019) discovered a gap in the process of technology commercialization that can be addressed by capturing the notion of technology value for productization. Productization here refers to the process of transforming a service or idea into a marketable product that can be sold to customers. The problem with this, however, is that technological services or ideas developed by developers to be marketed are not perceived as useful by users. This shows that there is a disparity between what technology developers consider valuable and what consumers actually value. Therefore, efforts to commercialize the technology more broadly are critical to improving users' perceptions of its importance (Chiesa & Frattini, 2011).

In addition to commercialization, product trialability is considered one of the factors that must be taken into account in an institutional context to ensure that consumers believe that the technology is useful and easy to use (Lubensky & Schmidbauer, 2020). Zhu and Chang (2014) found that perceived usefulness and perceived ease of use of technology-based services are two of the most important determinants of trial adoption. Trialability facilitates users in gaining a pre-adoption experience with the technology before committing to its usage. The short trial period allows users to recognize the technology's benefits and ease of use of the technology, which influences their decision to adopt it. Karahoca, Karahoca, and Aksöz (2018) reported that trialability affects users' perceptions of the usability of the technology, and that this effect may vary by gender. This clearly shows that trialability is one of the factors that determine individuals' use of technologies. Consequently, this aspect becomes an intriguing area of study, particularly when exploring farmers' perspectives on utilizing CSAT. However, from an agricultural technology perspective, little attention has been paid to this issue.

To ensure that users find the CSAT they use as useful and easy to use, facilitating conditions must be present. According to a study by Chung, Han, and Joun (2015) technology readiness and facilitating condition influence perceived usefulness and perceived ease of use. In addition, Yaseen, Bryceson, and Mungai (2018) emphasized the importance of facilitating conditions within the context of support institutions that can effectively support and positively influence farmers' adoption of modern technologies. This role of facilitating conditions proves to be particularly beneficial for smallholder farmers, ensuring that they perceive agricultural processes involving technology to be more accessible and beneficial. Based on previous studies related to the institutional context in forming user views about the advantages of using technology, several hypotheses were established related to the adoption of CSAT.

H1 : Commercialization significantly affects perceived usefulness of CSAT
H2 : Commercialization significantly affects perceived ease of use of CSAT
H3 : Trialability significantly influences perceived usefulness of CSAT
H4 : Trialability significantly influences perceived ease of use of CSAT
H5 : Facilitating condition significantly affects perceived usefulness of CSAT
H6 : Facilitating condition significantly affects perceived ease of use of CSAT

Individual Context

The initial hypotheses explain how the institutional context influences individuals' use of technology. This section then explores how the individual context influences the social context. Individual factors are measured by three variables: perceived usefulness, perceived ease of use and price value. Numerous studies show that social influence can affect individuals' adoption of technologies (AlSaleh & Thakur, 2019; Graf-Vlachy, Buhtz, & König, 2018; Wu & Chen, 2017). This study, however, focuses on how individual context affects social influence. Risselada, de Vries, and Verstappen (2018) found that individual assessments of the benefits of using technology and the convenience of technology on social media can influence more people to adopt technology. This indicates that individual reviews highlighting the benefits of the technology can trigger a social influence, leading to the expression of positive sentiments about the technology within the broader social community.

In addition, individuals with different orientations reacted differently to the selling price under the influence of varying amounts of information. Asymmetric information, for example, when the seller or product provider knows more about the benefits of the product, leads the seller or product provider to believe that the technology product is sold at a reasonable price, while the buyer believes that the technology product is overpriced and not worth buying (Lin, Lin, & Hung, 2008). Thus, if the consumer sees the benefits of the product, they will believe that the price offered represents value. However, the high price is unaffordable for smallholder farmers. Therefore, a competitive price or subsidy for CSAT is required to encourage farmers to utilize innovation (Long, Blok, & Poldner, 2017). Based on these explanations, several hypotheses were developed that link individual context to social influence have been developed.

H7 : Perceived usefulness significantly affects social influence about CSAT
H8 : Perceived ease of use significantly affects social influence about CSAT
H9 : Price value significantly affects social influence about CSAT

Reviews of technology products by individuals not only influence the social community, but also prompt environmentally conscious users to opt for the technology. The benefits of adopting technology are also seen as having the potential to increase environmental awareness (Fernández, Camargo, & Nascimento, 2019). Initially using technology to make work easier and reap the benefits that come from the output will increase environmental awareness. This happens because the user perceives the changes caused by the use and the price value of the technology (An, Di, Yao, & Jin, 2022). This will further motivate farmers to adopt CSAT. Therefore, based on the discussion of the factors in the individual context, three hypotheses are proposed.

H10 : Perceived usefulness significantly influences adoption of CSAT
H11 : Perceived ease of use significantly influences adoption of CSAT
H12 : Price value significantly influences adoption of CSAT

Social Context

The importance of the social context in encouraging farmers' adoption of CSAT is widely recognized. Discussions on how social factors influence technological use are notably broad and multi-dimensional. From the viewpoint of the UTAUT, social influence is understood as the extent to which significant others (like family, friends, or colleagues) shape an individual’s attitude towards embracing technology. Social influence is observed to increase technology usage and contribute to its growth (Venkatesh et al., 2012). This concept aligns with earlier perspectives from Bijker, Hughes, and Pinch (1987), who elucidated the development of technology, asserting that its trajectory is not solely determined by technical advancement but is also shaped by social factors. This is because technological evolution is an open-ended process, wherein various social groups have the opportunity to influence the design and functionality of technology to better meet societal needs.

Oudshoorn and Pinch (2005) further elaborate on the evolution of technology by focusing on the user dimension, highlighting how users not only shape technology but are also shaped by it in return. This concept is pivotal as it illustrates that the advent of specific technologies establishes new norms and cultures within social interactions. Supporting this notion, Korjonen-Kuusipuro et al. (2017), state that culture emerges from the interplay of behavioral practices and norms, which are both reflected in and influenced by daily life and user needs for technological solutions. The progression of such technologies is integral to fostering connections among individuals, communities, and society at large. In today's expanding digital realm, technology has birthed new cultural phenomena, particularly visible through social media and community reviews of technological products. These interactions transcend traditional cultural boundaries of ethnicity and geography, creating communities that converge to discuss and evaluate technologies relevant to them. This dynamic has given rise to a novel culture of interaction within specific social media communities, as identified by Benami and Carter (2021), forming what might be termed 'homogeneous zones' in these digital spaces.

Research by Risselada et al. (2018) indicates that individual evaluations and feedback on technology products, shared either on online purchasing sites or community forums, can significantly sway others’ decisions to adopt or discard a technology. Ocker (2010) notes that while positive, critical, and constructive comments can foster creativity, negative feedback may stifle it, engendering feelings of disappointment and disillusionment towards the technology. This dynamic of user feedback, ingrained in the culture of social media technology, reiterates the concept that technological product development is influenced by social creativity in seeking optimal solutions, as described by Bijker et al. (1987) and Oudshoorn and Pinch (2005). In the realm of CSAT, studies by Azadi et al. (2021) and Bazzana, Foltz, and Zhang (2022) reveal that social exchanges among farmers, particularly those revolving around the advantages of climate-smart systems and practices, significantly bolster CSAT usage. This dynamic is recognized as an integral element of interaction within the agricultural community. In this context, social influence is shaped by perceptions gleaned from community reviews and evaluations, particularly regarding a technology's practicality, ease of use and value for money. These aspects are deemed pivotal within the community, leading to a more widespread adoption of the technology. In light of this social context, the following hypotheses are proposed for exploration:

H13 : Social influence significantly affects CSAT adoption.

Environmental Context

The last aspect considered important is the awareness of farmers to protect the environment and ensure the sustainability of food security in the country by adopting CSAT. Numerous research findings suggest that CSAT adoption can have an impact on food security sustainability (Azadi et al., 2021; Bazzana et al., 2022; Hasan et al., 2018; Wekesa, Ayuyu, & Lagat, 2018). This is due to the fact that the use of CSAT effectively addresses climate change, enhances efficiency and productivity, and mitigates climate change-related challenges in agriculture. Simultaneously, this leads to an upsurge in agricultural production and contributes to the sustainability of food security. This demonstrates that raising awareness of CSAT is critical to ensuring environmental sustainability. The use of CSAT motivated is not only by the desire for profit or agricultural benefits, but also by an awareness of environmental protection that simultaneously increases the productivity of food production in the country. Therefore, a hypothesis is proposed.

H14 : CSAT adoption affects sustainable food security.

From the discussion of previous studies and the formulation of research hypotheses. Then a testable research model was developed. The study model depicted in Figure 1 is based on theories and contexts that include institutions, individuals, social, and the environment.

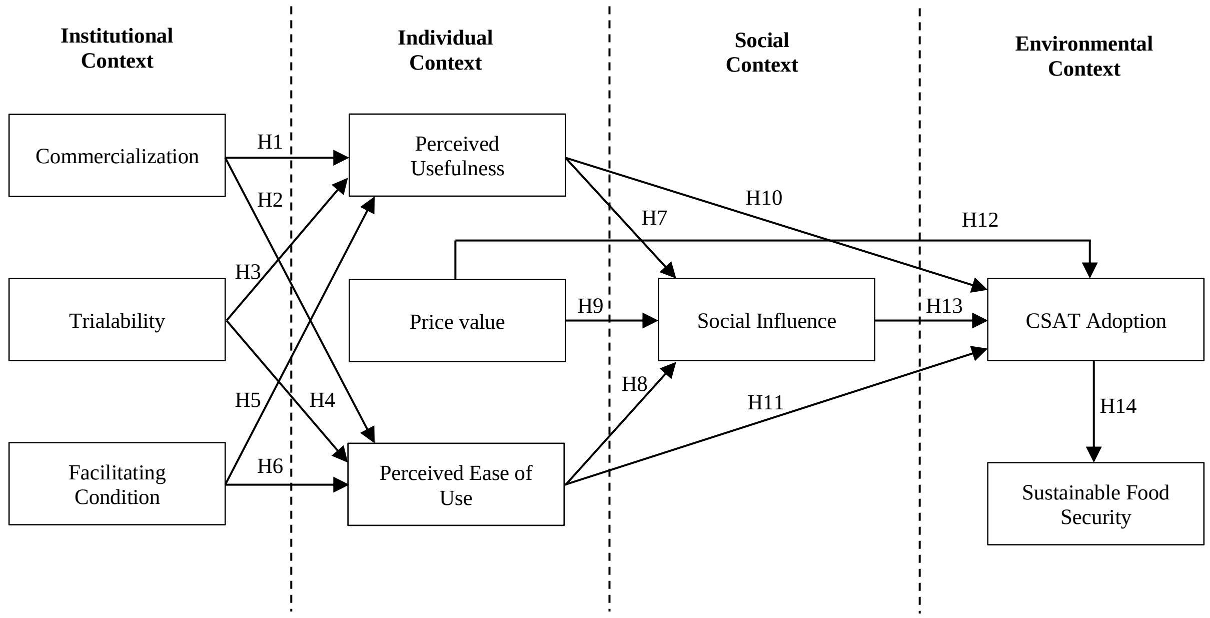

Figure 1. Research Model

METHODOLOGY

Research Design and Sample

This study employed a quantitative approach to collect data regarding the adoption of CSAT by farmers. The choice of a quantitative approach in this study stems from a positivist perspective, prioritizing objectivity in examining the causal relationships anticipated within the contexts of CSAT adoption. Data were collected from respondents using a cross-sectional design. A cross-sectional survey was chosen due to numerous factors noted by Spector (2019), including (1) the exploratory nature of the study, (2) not knowing the exact time frame, and (3) investigating the natural consequences for farmers. Since this study seemed to meet all three criteria, a cross-sectional research design was appropriate. The study sample consisted of farmers from Perlis, Kedah, and Perak states in northern Peninsular Malaysia. The sample size for the study was calculated using the G*Power application (Faul et al., 2007). Using a medium effect size of 0.15, an alpha level of 0.5, and a statistical power of 0.95, the minimum sample size required was 160. Data were collected from respondents using a questionnaire in the form of a booklet and an online survey (via a Google form) using stratified random sampling. After screening the data, 185 samples were found to be suitable for analysis. This number exceeded the minimum sample size required and was considered sufficient.

Instruments

A questionnaire was distributed to the respondents and used as a research instrument to measure each variable of the study model. The questionnaire consisted of five sections with fifty-four measurement items. The five sections included the respondent's profile (8 items), measurements for institutional context (12 items), individual context (16 items), social context (5 items), and environmental context (13 items).

The institutional context included three variables: commercialization, trialability and facilitating condition. The instrument for commercialization was adapted from Chiesa and Frattini (2011), for trialability from Fu et al. (2007), and facilitating condition from Wut, Lee and Xu (2022). For the individual context, it included three measurable variables: perceived usefulness, perceived ease of use and price value. The measures of perceived usefulness and perceived ease of use were adapted from Davis (1989) and Wang, Lew, Lau, and Leow (2019), while the price value was adapted from Venkatesh et al. (2012). Social context has only one variable, social influence, and the measures were adapted from Venkatesh et al. (2012) and Madigan et al. (2016). The last part is the environmental context, which has two variables: CSAT adoption and sustainable food security. The items on CSAT adoption were adapted from Sain et al. (2017) and Neufeldt et al. (2015), while sustainable food security was adapted from Azadi et al. (2021) and Bazzana et al. (2022).

As for the measurement scale, each item was measured using a five-point scale. The coding employed incorporates features of equidistance and also describes symmetry, making the five-point scale appropriate for multivariate analysis (Hair, Hult, Ringle, & Sarstedt, 2017). Considering the criteria, this study used the following coding categories: (1) strongly disagree, (2) disagree, (3) neither agree nor disagree, (4) agree, and (5) strongly agree. To ensure that the coding was symmetrical, the third scale was set to neutral, which is 'neither agree nor disagree', and the distance between each scale was considered equal to ensure that equidistance is attained.

Data Analysis

Partial Least Square Structural Equation Modeling (PLS-SEM) was chosen as the method of analysis for this study. SmartPLS, version 3.3.2, was used to assess the data for the analysis. This method was chosen for several reasons: (1) it is an exploratory study; (2) the goal is to predict the key factors that encourage farmers to adopt CSAT; and (3) a complex structural model is used to conduct the analysis (Hair et al., 2017). Based on these considerations, PLS-SEM is considered an appropriate method for data analysis. There are two stages for the analysis procedure: (1) the assessment of the measurement model and (2) the assessment of the structural model. After the first stage (measurement model) established the validity and reliability of the model, the assessment moved to the second stage (structural model) to test the hypotheses. The analytical report was prepared in accordance with the recommendations of Hair, Rusher, Sarstedt, and Ringle (2019) to ensure that the reporting of results was systematic, robust and comprehensive.

RESULT

Respondent Profiles

Of the total 185 responses, 124 (67%) were males and the remaining 61 (33%) were females. The age of the respondents ranged from 21 to 53 years, with the age distribution as follows: 42 respondents aged 21 to 30 years (22.7%), 81 respondents aged 31 to 40 years (43.8%) and 62 respondents aged 41 and above (33.5%). The largest proportion of respondents were Malay (87.5%), followed by Chinese (7.6%), other races (3.8%) and Indians (1.1%). In terms of agricultural experience, 44.3 percent had less than 5 years of experience, 36.8 percent had more than 5 to 10 years of experience and 18.9 percent had more than 10 years of experience. In terms of agricultural land area, 41.6 percent of the farmers have less than one acre, 24.9 percent have between one and five acres, 22.1 percent have between six and ten acres, and 11.4 per cent have more than ten acres. The landholdings of the respondents in this study closely align with the average size possessed by most Malaysian farmers, typically ranging from 2 to 3 hectares (equivalent to 4,942 to 7,413 acres). Additionally, both the median and mean figures for the respondents' land areas indicate that the farms of those participating in the study are generally around 5 acres in size. This profile indicates that not all respondents were smallholder farmers; there were also farmers with medium and large land sizes. Therefore, a wide range of farmers were represented in this analysis in terms of their perspectives on the adoption of CSAT.

Assessment of Measurement Model

In the measurement model assessment stage, the built model is assessed to ensure that it is valid and has good reliability before hypothesis testing is carried out. Four aspects are evaluated in this stage: indicator reliability, internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2017). For the evaluation of indicator reliability, the factor loading values for each construct are assessed. The factor loading threshold with a value greater than 0.708 is considered to have good indicator reliability (Hair et al., 2019). Three indicators, T1, FC2 and PV1, which had factor loading values below 0.708 during this evaluation process were omitted from the model. As shown in Table 1, the remaining indicators have factor loading values ranging from 0.729 to 0.943, indicating that the reliability of the indicators for a given construct is good.

Next, the internal consistency reliability was assessed using composite reliability and Cronbach's alpha. Both composite reliability and Cronbach's alpha have the same threshold values. For exploratory research, values between 0.60 and 0.70 are considered 'acceptable,' while values between 0.70 and 0.90 are considered 'satisfactory to good' (Hair et al., 2019). However, concerns arise when reliability values exceed 0.95, indicating potential issues with response patterns and redundant items within the construct. The results, as shown in Table 1, indicate that the composite reliability values range from 0.912 to 0.947, while Cronbach's alpha ranges from 0.877 to 0.936. These findings demonstrate that the constructed model exhibits good internal consistency reliability.

Table 1. Construct validity and reliability

Construct	Indicator	Loadings	Composite Reliability	Cronbach's Alpha	AVE
Commercialization	C1	0.901	0.915	0.877	0.730
	C2	0.834			
	C3	0.871			
	C4	0.808			
Trialability	T2	0.890	0.945	0.912	0.851
	T3	0.943			
	T4	0.935			
Facilitating Conditions	FC1	0.902	0.935	0.896	0.826
	FC3	0.942			
	FC4	0.894			
Perceived Usefulness	PU1	0.898	0.931	0.907	0.730
	PU2	0.907			
	PU3	0.783			
	PU4	0.905			
	PU5	0.768			
Perceived Ease of Use	PE1	0.800	0.946	0.929	0.778
	PE2	0.907			
	PE3	0.906			
	PE4	0.875			
	PE5	0.917			
Price Value	PV2	0.729	0.912	0.884	0.675
	PV3	0.807			
	PV4	0.853			
	PV5	0.834			
	PV6	0.876			
Social Influence	SI1	0.741	0.915	0.883	0.684
	SI2	0.822			
	SI3	0.863			
	SI4	0.829			
	SI5	0.872			
CSAT Adoption	CSAT1	0.783	0.947	0.936	0.691
	CSAT2	0.848			
	CSAT3	0.778			
	CSAT4	0.773			
	CSAT5	0.836			
	CSAT6	0.895			
	CSAT7	0.901			
	CSAT8	0.824			
Sustainable Food Security	SFS1	0.902	0.940	0.923	0.760
	SFS2	0.922			
	SFS3	0.889			
	SFS4	0.739			
	SFS5	0.895			

Convergent validity was assessed using the average variance extracted (AVE) as the metric. An AVE threshold of 0.50 or higher indicates that the construct captures at least 50% of the variance of its items (Hair et al., 2019). The analysis reveals that all constructs possess an AVE value exceeding 0.50, ranging from 0.675 to 0.851. This underscores the constructs' strong convergent validity, indicating that over half of the item variance can be accounted for within each construct.

Next, discriminant validity was assessed to determine the extent to which each construct in the model differed empirically from the others. According to Henseler, Ringle, and Sarstedt (2015), the heterotrait-monotrait (HTMT) ratio of correlations offers a more robust measure of discriminant validity compared to the traditional Fornell-Larcker criterion. This is especially important when indicator loadings on the construct exhibit only slight differences. Consequently, the HTMT was employed in this study to evaluate discriminant validity. In the proposed HTMT analysis, a value of 0.90 or higher indicates a lack of discriminant validity. As shown in Table 2, the HTMT values for all constructs ranged from 0.363 to 0.854, indicating that the constructed model indeed demonstrated discriminant validity. Thus, based on the measurement model analysis, it can be concluded that the constructed model achieved an acceptable level of validity and reliability.

Table 2. Discriminant validity using HTMT ratio

	C	T	FC	PU	PE	PV	SI	CSAT	SFS
Commercialization									
Trialability	0.548								
Facilitating Conditions	0.603	0.436							
Perceived Usefulness	0.608	0.802	0.450						
Perceived Ease of Use	0.560	0.423	0.522	0.669					
Price Value	0.574	0.512	0.471	0.645	0.738				
Social Influence	0.680	0.783	0.525	0.854	0.566	0.544			
CSAT Adoption	0.427	0.421	0.363	0.606	0.605	0.613	0.666		
Sustainable Food Security	0.433	0.457	0.453	0.600	0.542	0.620	0.617	0.671	

Assessment of Structural Model

Once it was confirmed that the constructed model had achieved a satisfactory level of validity and reliability in the assessment of the measurement model, the evaluation shifted to the structural model. During this stage, various aspects were examined. Prior to testing the significance and relevance of the relationships within the structural model through hypothesis testing, it was essential to ensure the absence of collinearity issues within the model. To address the collinearity concern, the variance inflation factor (VIF) was calculated and analyzed within the structural model. A VIF value below 5.0 is typically considered indicative of a lack of collinearity issues (Hair et al., 2019). Based on the obtained results, the VIF values for the constructs within the model ranged from 1.00 to 3.198. These findings affirm that the constructed model did not exhibit critical collinearity issues.

Table 3. Structural relationship and hypotheses results

Hypo.	Path	Coeff.	f^2	*p*-values	95% Conf. Int.	Supported?
H1	C → PU	0.233	0.083	0.010**	[0.054, 0.420]	Yes
H2	C → PE	0.319	0.097	0.001**	[0.146, 0.517]	Yes
H3	T → PU	0.599	0.640	0.000***	[0.439, 0.775]	Yes
H4	T → PE	0.163	0.030	0.026*	[0.029, 0.312]	Yes
H5	FC → PU	0.053	0.005	0.524	[-0.119, 0.209]	No
H6	FC → PE	0.237	0.058	0.009**	[0.046, 0.399]	Yes
H7	PU → SI	0.745	0.801	0.000***	[0.579, 0.893]	Yes
H8	PE → SI	0.040	0.000	0.723	[-0.141, 0.276]	No
H9	PV → SI	0.028	0.001	0.755	[-0.156, 0.186]	No
H10	PU → CSAT	0.041	0.005	0.942	[-0.319, 0.327]	No
H11	PE → CSAT	0.355	0.115	0.026*	[0.155, 0.585]	Yes
H12	PV → CSAT	0.204	0.041	0.080	[-0.036, 0.430]	No
H13	SI → CSAT	0.395	0.142	0.008**	[0.099, 0.668]	Yes
H14	CSA → SFS	0.676	0.841	0.000***	[0.550, 0.817]	Yes

Note(s): *$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$

Hypothesis tests were subsequently conducted to ascertain the significance and relevance of the relationships within the structural model. The estimation of path coefficients representing the hypothesized relationships between the constructs utilized 5,000 bootstrap samples. Out of the fourteen hypotheses tested, nine exhibited statistically significant results, while five yielded non-significant outcomes. Within the institutional context, all hypotheses yielded significant results, except for the facilitating condition hypothesis concerning perceived usefulness ($\beta = 0.053$, $p > 0.05$). Consequently, H5 was rejected. However, both commercialization's impact on perceived usefulness ($\beta = 0.233$, $p < 0.01$) and perceived ease of use ($\beta = 0.319$, $p < 0.01$) were statistically significant, supporting hypotheses H1 and H2, respectively. Furthermore, the effects of trialability on perceived usefulness ($\beta = 0.599$, $p < 0.001$) and perceived ease of use ($\beta = 0.163$, $p < 0.05$) were also significant, thereby confirming hypotheses H3 and H4. In contrast, the effect of the facilitating condition was only significant for perceived ease of use (β = 0.237, p < 0.01), providing support for hypothesis H6.

Within the individual context, three factors were measured: price value, perceived usefulness, and perceived ease of use. However, the results revealed that neither price value (β = 0.028, p > 0.05) nor perceived ease of use (β = 0.040, p > 0.05) exerted a significant effect on the social influence driving farmers' adoption of CSAT. Consequently, hypotheses H8 and H9 were rejected. On the other hand, perceived usefulness was found to have a significant impact on social influence (β = 0.745, p < 0.001), supporting hypothesis H7. From the perspective of the individual context on CSAT adoption, only perceived ease of use yielded a significant result (β = 0.355, p < 0.05), thus supporting H11. However, perceived usefulness and price value yielded insignificant results (β = 0.041, p > 0.05) and (β = 0.204, p > 0.05), respectively, leading to the rejection of hypotheses H10 and H12. Within the social context, the factor of social influence demonstrated a significant impact on CSAT adoption (β = 0.395, p < 0.01), supporting H13. This indirectly suggests that perceived usefulness, mediated through social influence, has an indirect effect on CSAT adoption (β = 0.288, p < 0.05), illustrating the role of social influence as a mediator in informing farmers about the benefits of CSAT. In the environmental context, farmers' perspective unquestionably revealed a significant impact of CSAT adoption on the sustainability of food security (β = 0.676, p < 0.001), thus supporting H14.

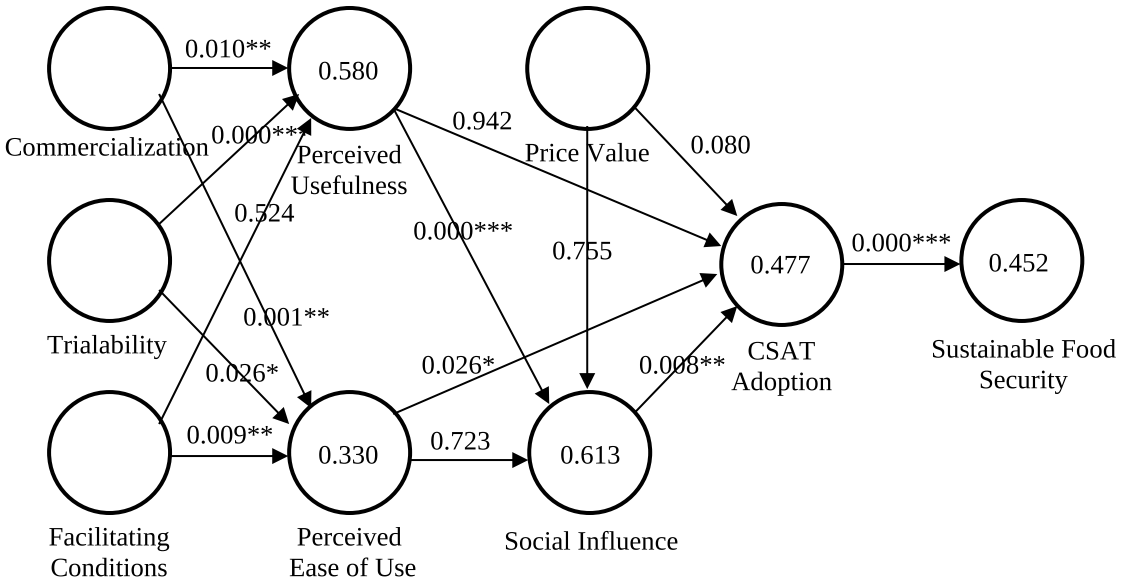

Figure 2. Result of PLS analysis

Following the hypothesis testing, the coefficient of determination (R^2) value was computed to determine the extent of variance explained by each endogenous construct. In this study, five endogenous constructs were examined, and as suggested by Hair et al. (2019), R^2

values of 0.75, 0.50, and 0.25 correspond to substantial, moderate, and weak explanatory power, respectively. The findings of the analysis revealed that two endogenous constructs exhibited moderate predictive power, with R^2 values falling within the range of 0.50 to 0.74. Meanwhile, three endogenous constructs displayed weak predictive power, with R^2 values ranging from 0.25 to 0.49. Specifically, the endogenous construct with the highest R^2 value was social influence ($R^2 = 0.613$), followed by perceived usefulness ($R^2 = 0.580$), CSAT adoption ($R^2 = 0.477$), sustainable food security ($R^2 = 0.452$), and perceived ease of use ($R^2 = 0.330$).

This study further assessed the effect size (f^2) of the exogenous constructs, which contributes to the predictive power of the endogenous construct R^2. As a general guideline, effect sizes greater than 0.02, 0.15, and 0.35 indicate small, medium, and large f^2 values, respectively (Hair et al., 2019). The findings of the study indicate that three constructs, namely trialability → perceived usefulness ($f^2 = 0.640$), perceived usefulness → social influence ($f^2 = 0.801$), and CSAT adoption → sustainable food security ($f^2 = 0.841$), exhibited substantial effect sizes (f^2). These constructs significantly contributed to the variance change and predictive power of the endogenous construct R^2. Table 3 provides an overview of the effect sizes of other exogenous constructs, which were found to have only a small effect size.

Furthermore, the predictive accuracy of the PLS path model was assessed using Stone-Geisser's Q^2, which measures the predictive relevance. Based on the blindfolding results with an omission distance of seven, all endogenous constructs exhibited Q^2 values greater than zero. As per the guideline, Q^2 values above 0, 0.25, and 0.50 indicate small, medium, and large predictive relevance of the PLS path model, respectively (Hair et al., 2019). In this study, all endogenous constructs demonstrated medium predictive relevance, with Q^2 values ranging from 0.255 to 0.419. These findings confirm that the developed model possesses medium predictive relevance. The final step in evaluating the structural model involved assessing its out-of-sample predictive power using $PLS_{predict}$ (Shmueli et al., 2019). Through a 10-fold cross-validation, all $Q^2_{predict}$ values were found to be greater than zero, indicating that the model outperformed the naïve benchmark. By comparing the PLS-RMSE and LM-RMSE indicators, it was observed that only a minority of PLS-RMSE values resulted in higher prediction errors than LM-RMSE, indicating that the model exhibited medium predictive power.

DISCUSSIONS

Based on the results of the study, the model developed has medium predictive power in determining the factors that drive farmers to adopt CSAT. Since this is an exploratory study on the causal-predictive relationship in a complex model, medium predictive power is considered good in explaining the factors for adoption of CSAT among farmers. In terms of institutional context, the study found that the role of institutions is important in informing farmers about the benefits and advantages of adopting CSAT in their agricultural production. This finding is consistent with previous research by Mazhar et al. (2021), Fusco et al. (2020), and Totin et al. (2018), who found that the role of institutions is an important factor in CSAT adoption.

However, this research goes beyond the conventional understanding of institutions and explores their nuanced capabilities, particularly in fostering commercialization. This is substantiated by the significant relationship observed between the commercialization factor and farmers' perception of the usefulness of CSAT, as well as the technology's ability to enhance task performance. Therefore, it is imperative to further expand and develop the aspect of commercialization to enhance farmers' awareness of the available technologies that can enhance agricultural productivity and provide them with benefits. As highlighted by Kim et al. (2019), addressing the information asymmetry between developers and customers regarding the perceived value of a technology through commercialization is a key factor in promoting the technology's recognition for its functional benefits.

Furthermore, the trialability factor holds significant importance in instilling farmers' confidence in the benefits of technology and providing them with firsthand experience of how it can simplify their tasks and work processes. This significance becomes evident as the results indicate a substantial relationship between trialability and both perceived usefulness and perceived ease of use. The substantial effect size of trialability on perceived usefulness further emphasizes the critical role of this factor in building confidence in the benefits of CSAT. This argument finds support in previous research, which has demonstrated that when consumers have the opportunity to try a product, their confidence in its quality increases, regardless of whether it aligns precisely with their perceived value (Kim et al., 2019). Additionally, a trial version has the potential to reshape the user's mindset and enhance their intention to further explore the features and benefits of the technology product (Chiesa & Frattini, 2011).

Regarding the facilitating condition, it is evident that it does not directly influence perceived usefulness but solely impacts perceived ease of use. This is because the purpose of the facilitating condition is to provide support, education, and assistance to users in utilizing the technology more effectively, without necessarily making them explicitly aware of the benefits. If users perceive a particular technology as challenging to use and require facilitating conditions, they are likely to perceive it as less useful. This finding aligns with the research conducted by Chung et al. (2015), which emphasized the significance of facilitating conditions in relation to perceived ease of use rather than perceived usefulness. Hence, it becomes apparent that facilitating conditions have a greater impact on perceived ease of use compared to perceived usefulness.

In the individual context, it was observed that perceived usefulness had a significant impact on social influence, whereas price value and perceived ease of use did not exhibit significance in relation to social influence. This can be attributed to the fact that farmers prioritize the benefits and advantages offered by technology in enhancing their agricultural productivity. The substantial gains in productivity resulting from these technology benefits contribute to an increase in their social influence. These findings are consistent with the research conducted by Risselada et al. (2018), who identified that when social media users review a product's benefits, it enhances social influence towards using the product. Hence, the results of this study indicate that CSAT operates in a similar manner, with its benefits exerting a comparable effect on social influence.

On the contrary, ease of use is not the primary influencing factor for farmers when it comes to exerting influence on society. This can be attributed to their familiarity with traditional production methods (Akouwerabou et al., 2022). However, an interesting finding emerged that perceived ease of use does impact CSAT adoption. It is understandable that farmers are more likely to adopt technology as a CSAT if it is user-friendly. Nevertheless, ease of use does not significantly influence the social impact of agriculture, marking a notable distinction in this regard. In comparison to other studies, such as the research conducted by Risselada et al. (2018), user reviews on ease of use do not appear to exert a significant influence on the adoption of CSAT. Similarly, price value does not affect social influence in agriculture or CSA practices. This can be attributed to the presence of information asymmetries associated with CSA technology. Farmers evaluate the value of CSA technology and practices differently, depending on their perception of price value as being valuable or not, as highlighted by Kim et al. (2019). This difference can potentially stem from the heterogeneity between small and large farmers, although it was not observed within the scope of this study.

In the social context, social influence acts as a mediator between perceived usefulness and CSAT adoption. This finding is intriguing as it suggests that while farmers acknowledge the benefits of CSAT, their adoption of it is generally influenced by the social community. In contrast, if the technology is perceived as ease of use, farmers are more likely to continue utilizing it. However, to strengthen CSAT adoption, social influence must serve as a facilitator in promoting the benefits. This result aligns with the studies conducted by Azadi et al. (2021) and Bazzana et al. (2022), which highlight the influential role of the social community among farmers in adopting CSAT. In this context, the institutional framework plays a crucial role by enhancing opportunities for testing CSAT and facilitating their commercialization, enabling farmers to maximize the benefits and broaden their sphere of influence. Regarding the environmental context, CSAT undeniably contribute to achieving sustainable food security, as supported by the significant results and substantial effect sizes observed between CSAT adoption and food security sustainability (Bazzana et al., 2022; Hasan et al., 2018; Wekesa et al., 2018). These findings indicate that farmers recognize the potential of CSAT in increasing productivity and promoting the sustainability of food security.

While this study has delineated the effects of institutional, individual, social, and environmental contexts on the adoption of CSAT and sustainable food security, its findings are confined to farmers in Malaysia. Consequently, it is plausible that variations in geographical factors, national economic policies, and diverse cultural practices might yield differing outcomes. Therefore, in advancing understanding and awareness about CSAT adoption and climate-change responsiveness, this study puts forth several recommendations for future research. One such recommendation is to conduct comparative analyses across different societal segments, such as varied ethnic groups, which may possess distinct cultures and operational methods. Future research could also concentrate on small-scale farmers, who are often perceived as less capable of implementing CSAT. Additionally, these findings could be expanded to explore the roles of government entities, private sector organizations, and NGOs in promoting CSAT. This exploration might include examining perspectives related to incentives, subsidies, and up-skilling programs tailored for CSAT usage among farmers.

CONCLUSIONS

This study has highlighted the significant role of institutions in influencing user perceptions, particularly in relation to commercialization and trialability. Commercialization serves as a crucial avenue for educating farmers about the benefits associated with technology, thereby informing them of the available technologies capable of enhancing productivity. To enhance farmers' confidence in the benefits of technology, it is imperative for them to gain hands-on experience with it. Therefore, farmers should be provided with opportunities to engage with state-of-the-art agricultural technology, allowing them to experiment and explore its potential. The benefits arising from such experimentation will not only impact the agricultural community but also drive the adoption of CSAT among farmers, ultimately contributing to the sustainability of food security.

Furthermore, the individual context plays a crucial role in ensuring that farmers perceive CSA technology as useful and ease of use. This emphasizes the importance of the initial processes of commercialization and trialability, which help address information asymmetry regarding the value, benefits, and features of CSAT. The benefits derived from these processes can be further disseminated to exert social influence within the community, thereby promoting the adoption of CSAT among farmers. Therefore, to effectively accomplish this objective, it is crucial to foster synergies among the government, private sector, and non-governmental organizations (NGOs) in establishing an efficient institutional structure that supports and promotes CSAT within the agricultural sector.

REFERENCES

Akouwerabou, D. B., Zanré, P. K., Savadogo, K., & Kaboré, P. J. W. (2022). Promoting farmers’ adoption of climate-smart agricultural technologies in Burkina Faso: The role of coordination along the value chain. *International Journal of Agricultural Resources, Governance and Ecology*, 18(3), 287–308. https://doi.org/10.1504/IJARGE.2022.124650

Alkhwaldi, A., & Kamala, M. (2017). Why do users accept innovative technologies? A critical review of models and theories of technology acceptance in the information system literature. *Journal of Multidisciplinary Engineering Science and Technology*, 4(8), 2458–9403.

AlSaleh, D., & Thakur, R. (2019). Impact of cognition, affect, and social factors on technology adoption. *International Journal of Technology Marketing*, 13(2), 178–200. https://doi.org/10.1504/IJTMKT.2019.102266

An, J., Di, H., Yao, M., & Jin, S. (2022). The role of payment technology innovation in environmental sustainability: Mediation effect from consumers’ awareness to practice. *Frontiers in Environmental Science*, 10, 881293. https://doi.org/10.3389/fenvs.2022.881293

Andrieu, N., Sogoba, B., Zougmore, R., Howland, F., Samake, O., Bonilla-Findji, O., Lizarazo, M., Nowak, A., Dembele, C., & Corner-Dolloff, C. (2017). Prioritizing investments for climate-smart agriculture: Lessons learned from Mali. *Agricultural Systems*, 154, 13–24. https://doi.org/10.1016/j.agsy.2017.02.008

Antwi-Agyei, P., Abalo, E. M., Dougill, A. J., & Baffour-Ata, F. (2021). Motivations, enablers and barriers to the adoption of climate-smart agricultural practices by smallholder farmers: Evidence from the transitional and savannah agroecological zones of Ghana. *Regional Sustainability*, 2(4), 375–386. https://doi.org/10.1016/j.regsus.2022.01.005

Anuga, S. W., Gordon, C., Boon, E., & Surugu, J. M. (2019). Determinants of Climate Smart Agriculture (CSA) adoption among smallholder food crop farmers in the Techiman Municipality, Ghana. *Ghana Journal of Geography*, 11(1), 124–139.

Autio, A., Johansson, T., Motaroki, L., Minoia, P., & Pellikka, P. (2021). Constraints for adopting climate-smart agricultural practices among smallholder farmers in Southeast Kenya. *Agricultural Systems*, 194, 103284. https://doi.org/10.1016/j.agsy.2021.103284

Azadi, H., Moghaddam, S. M., Burkart, S., Mahmoudi, H., Passel, S.V., Kurban A., & Lopez-Carr, D. (2021). Rethinking resilient agriculture: From Climate-Smart Agriculture to Vulnerable-Smart Agriculture. *Journal of Cleaner Production*, 319, 128602. https://doi.org/10.1016/j.jclepro.2021.128602

Bazzana, D., Foltz, J., & Zhang, Y. (2022). Impact of climate smart agriculture on food security: An agent-based analysis. *Food Policy*, 111, 102304. https://doi.org/10.1016/j.foodpol.2022.102304

Bijker, W. E., Hughes, T. P., & Pinch T. J. (1987). *The social construction of technological systems: New directions in the sociology and history of technology*. Massachusetts: MIT Press

Benami, E., & Carter, M. R. (2021). Can digital technologies reshape rural microfinance? Implications for savings, credit, & insurance. *Applied Economic Perspectives and Policy*, 43(4), 1196-1220. https://doi.org/10.1002/aepp.13151

Casey, J., Bisaro, A., Valverde, A., Martinez, M., & Rokitzki, M. (2021). *Private finance investment opportunities in climate-smart agriculture technologies*. Retrieved on May 25, 2023, from https://www.casaprogramme.com/wp-content/uploads/2021/10/Private-finance-investment-opportunities-in-climate-smart-agriculture-technologies.pdf

Chiesa V., & Frattini, F. (2011). Commercializing technological innovation: Learning from failures in high-tech markets. *Journal of Product Innovation Management*, 28(4), 437–454. https://doi.org/10.1111/j.1540-5885.2011.00818.x

Chung, N., Han, H., & Joun, Y. (2015). Tourists' intention to visit a destination: The role of augmented reality (AR) application for a heritage site. *Computers in Human Behavior*, 50, 588–599. https://doi.org/10.1016/j.chb.2015.02.068

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–339. https://doi.org/10.2307/249008

Dey, K., & Mishra, P. K. (2022). Mainstreaming blended finance in climate-smart agriculture: Complementarity, modality, and proximity. *Journal of Rural Studies*, 92, 342–353. https://doi.org/10.1016/j.jrurstud.2022.04.011

Dwivedi, Y. K., Mustafee, N., Carter, L. D., & Williams, M. D. (2010). A bibliometric comparison of the usage of two theories of IS/IT acceptance (TAM and UTAUT). In *AMCIS 2010 Proceedings*, 183. https://aisel.aisnet.org/amcis2010/183

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, 39(2), 175–191. https://doi.org/10.3758/BF03193146

Fernández, A. H., Camargo, C. D. B., & Nascimento, M. S. L. D. (2019). Technologies and environmental education: A beneficial relationship. *Research in Social Sciences and Technology*, 4(2), 13–30.

Fu, Z., Yue, J., Li, D., Zhang, X., Zhang, L., & Gao, Y. (2007). Evaluation of learner adoption intention of e-learning in China: A methodology based on perceived innovative attributes. *New Zealand Journal of Agricultural Research*, 50(5), 609–615. https://doi.org/10.1080/00288230709510329

Fusco, G., Melgiovanni, M., Porrini, D., & Ricciardo, T. M. (2020). How to improve the diffusion of climate-smart agriculture: What the literature tells us. *Sustainability*, 12(12), 5168. https://doi.org/10.3390/su12125168

Graf-Vlachy, L., Buhtz, K., & König, A. (2018). Social influence in technology adoption: Taking stock and moving forward. *Management Review Quarterly*, 68, 37–76. https://doi.org/10.1007/s11301-017-0133-3

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM),* New York: Sage.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hasan, M. K., Desiere, S., D'Haese, M., & Kumar, L. (2018). Impact of climate-smart agriculture adoption on the food security of coastal farmers in Bangladesh. *Food Security*, 10(4), 1073–1088. https://doi.org/10.1007/s12571-018-0824-1

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43, 115–135. https://doi.org/10.1007/s11747-014-0403-8

Kabir, K. H., Sarker, S., Uddin, M. N., Leggette, H. R., Schneider, U. A., Darr, D., & Knierim, A. (2022). Furthering climate-smart farming with the introduction of floating agriculture in Bangladeshi wetlands: Successes and limitations of an innovation transfer. *Journal of Environmental Management*, 323, 116258. https://doi.org/10.1016/j.jenvman.2022.116258

Karahoca, A., Karahoca, D., & Aksöz, M. (2018). Examining intention to adopt to internet of things in healthcare technology products. *Kybernetes*, 47(4), 742-770. https://doi.org/10.1108/K-02-2017-0045

Khoza, S., de Beer, L. T., van Niekerk, D. & Nemakonde, L. (2021). A gender-differentiated analysis of climate-smart agriculture adoption by smallholder farmers: Application of the extended technology acceptance model. *Gender, Technology and Development*, 25(1), 1–21. https://doi.org/10.1080/09718524.2020.1830338

Kim, M., Park, H., Sawng, Y. W., & Park, S. Y. (2019). Bridging the gap in the technology commercialization process: Using a three-stage technology-product-market model. *Sustainability*, 11(22), 6267. https://doi.org/10.3390/su11226267

Korjonen-Kuusipuro, K., Hujala, M., Pätäri, S., Bergman, J. P., & Olkkonen, L. (2017). The emergence and diffusion of grassroots energy innovations: Building an interdisciplinary approach. *Journal of Cleaner Production*, 140, 1156-1164. https://doi.org/10.1016/j.jclepro.2016.10.047

Lee, J. (2017). Farmer participation in a climate-smart future: Evidence from the Kenya agricultural carbon market project. *Land use policy*, 68, 72–79. https://doi.org/10.1016/j.landusepol.2017.07.020

Lin, C. H., Lin, H. M., & Hung, A. L. (2008). Social value orientation and information level in selling prices. *Social Behavior and Personality*, 36(7), 933–940. https://doi.org/10.2224/sbp.2008.36.7.933

Long, T. B., Blok, V., & Poldner, K. (2017). Business models for maximising the diffusion of technological innovations for climate-smart agriculture. *International Food and Agribusiness Management Review*, 20(1), 5–23. https://doi.org/10.22434/IFAMR2016.0081

Lubensky, D., & Schmidbauer, E. (2020). Free product trials: Disclosing quality and match value. *Economic Inquiry*, 58(4), 1565–1576. https://doi.org/10.1111/ecin.12858

Madigan, R., Louw, T., Dziennus, M., Graindorge, T., Ortega, E., Graindorge, M., & Merat, N. (2016). Acceptance of Automated Road Transport Systems (ARTS): An Adaptation of the UTAUT Model. *Transportation Research Procedia*, 14, 2217–2226. https://doi.org/10.1016/j.trpro.2016.05.237

Makate, C. (2019). Effective scaling of climate smart agriculture innovations in African smallholder agriculture: A review of approaches, policy and institutional strategy needs. *Environmental Science and Policy*, 96, 37–51. https://doi.org/10.1016/j.envsci.2019.01.014

Mashi, S. A., Inkani, A. I., & Oghenejabor, O. D. (2022). Determinants of awareness levels of climate smart agricultural technologies and practices of urban farmers in Kuje, Abuja, Nigeria. *Technology in Society*, 70, 102030. https://doi.org/10.1016/j.techsoc.2022.102030

Mazhar, R., Ghafoor, A., Xuehao, B., & Wei, Z. (2021). Fostering sustainable agriculture: Do institutional factors impact the adoption of multiple climate-smart agricultural practices among new entry organic farmers in Pakistan? *Journal of Cleaner Production*, 283, 124620. https://doi.org/10.1016/j.jclepro.2020.124620

Meshesha, A. T., Birhanu, B. S., & Ayele, M. B. (2022). Effects of perceptions on adoption of climate-smart agriculture innovations: Empirical evidence from the upper Blue Nile Highlands of Ethiopia. *International Journal of Climate Change Strategies and Management*, 14(3), 293–311. https://doi.org/10.1108/IJCCSM-04-2021-0035

Morgan, E. H., Severs, M. M., Hanson, K. L., McGuirt, J., Becot, F., Wang, W., Kolodinsky, J., Sitaker, M., Pitts, S. B. J., Ammerman, A., & Seguin, R. A. (2018). Gaining and maintaining a competitive edge: Evidence from CSA members and farmers on local food marketing strategies. *Sustainability*, 10(7), 2177. https://doi.org/10.3390/su10072177

Neufeldt, H., Negra, C., Hancock, J., Foster, K., Nayak, D., & Singh, P. (2015). *Scaling up climate-smart agriculture: lessons learned from South Asia and pathways for success*. Retrieved on May 28, 2023, https://apps.worldagroforestry.org/downloads/Publications/PDFS/WP15720.pdf

Nyasimi, M., Kimeli, P., Sayula, G., Radeny, M., Kinyangi, J., & Mungai, C. (2017). Adoption and dissemination pathways for climate-smart agriculture technologies and practices for climate-resilient livelihoods in Lushoto, Northeast Tanzania. *Climate*, 5(3), 63. https://doi.org/10.3390/cli5030063

Ocker, R. (2010). Promoting Group Creativity in Upstream Requirements Engineering. *Human Technology*, 6(1), 55–70. https://doi.org/10.17011/ht/urn.20105241907

Oudshoorn, N., & Pinch, T. (2005). *How users matter: The co-construction of users and technology*. Massachusetts: MIT Press

Ouédraogo, M., Houessionon, P., Zougmoré, R. B., & Partey, S. T. (2019). Uptake of climate-smart agricultural technologies and practices: Actual and potential adoption rates in the climate-smart village site of Mali. *Sustainability*, 11(17), 4710. https://doi.org/10.3390/su11174710

Rahman, H. A. (2009). Global climate change and its effects on human habitat and environment in Malaysia. *Malaysian Journal of Environmental Management*, 10(2), 17–32.

Raile, E. D., Young, L. M., Kirinya, J., Bonabana-Wabbi, J., & Raile, A. N. W. (2021). Building public will for climate-smart agriculture in Uganda: Prescriptions for industry and policy. *Journal of Agricultural and Food Industrial Organization*, 19(1), 39–50. https://doi.org/10.1515/jafio-2021-0012

Raj, S., & Garlapati, S. (2020). *Extension and advisory services for climate-smart agriculture*. In V. Venkatramanan, S. Shah & R. Prasad (Eds.), Global climate change: Resilient and smart agriculture (pp. 273–299), Singapore: Springer. https://doi.org/10.1007/978-981-32-9856-9_13

Risselada, H., de Vries, L., & Verstappen, M. (2018). The impact of social influence on the perceived helpfulness of online consumer reviews. *European Journal of Marketing*, 52(3–4), 619–636. https://doi.org/10.1108/EJM-09-2016-0522

Sain, G., Loboguerrero, A. M., Corner-Dolloff, C., Lizarazo, M., Nowak, A., Martínez-Barón, D., & Andrieu, N. (2017). Costs and benefits of climate-smart agriculture: The case of the Dry Corridor in Guatemala. *Agricultural Systems*, 151, 163–173. https://doi.org/10.1016/j.agsy.2016.05.004

Sair, S. A., & Danish, R. Q. (2018). Effect of performance expectancy and effort expectancy on the mobile commerce adoption intention through personal innovativeness among Pakistani consumers. *Pakistan Journal of Commerce and Social Science*, 12(2), 501–520.

Scott, S. D., Plotnikoff, R. C., Karunamuni, N., Bize, R., & Rodgers, W. (2008). Factors influencing the adoption of an innovation: An examination of the uptake of the Canadian Heart Health Kit (HHK). *Implementation Science*, 3(41), 1–8. https://doi.org/10.1186/1748-5908-3-41

Senyolo, M. P., Long, T. B., Blok, V., & Omta, O. (2018). How the characteristics of innovations impact their adoption: An exploration of climate-smart agricultural innovations in South Africa. *Journal of Cleaner Production*, 172, 3825–3840. https://doi.org/10.1016/j.jclepro.2017.06.019

Shahbaz, P., ul Haq, S., Abbas, A., Batool, Z., Alotaibi, B. A., & Nayak, R. K. (2022). Adoption of climate smart agricultural practices through women involvement in decision making process: Exploring the role of empowerment and innovativeness. *Agriculture*, 12(8), 1161. https://doi.org/10.3390/agriculture12081161

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, 53(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

Spector, P. E. (2019). Do not cross me: Optimizing the use of cross-sectional designs. *Journal of Business and Psychology*, 34, 125–137. https://doi.org/10.1007/s10869-018-09613-8

Statista Search Department. (2022). Contribution of agriculture to the gross domestic product (GDP) of Malaysia from 2015 to 2021. *Statista*. Retrieved on May 23, 2023, from https://www.statista.com/statistics/952990/malaysia-agriculture-share-of-gdp

Totin, E., Segnon, A. C., Schut, M., Affognon, H., Zougmoré, R. B., Rosenstock, T., & Thornton, P. K. (2018). Institutional perspectives of climate-smart agriculture: A systematic literature review. *Sustainability*, 10(6), 1990. https://doi.org/10.3390/su10061990

Tsige, M., Synnevåg, G., & Aune, J. B. (2020). Gendered constraints for adopting climate-smart agriculture amongst smallholder Ethiopian women farmers. *Scientific African*, 7, e00250. https://doi.org/10.1016/j.sciaf.2019.e00250

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178. https://doi.org/10.2307/41410412

Waaswa, A., Nkurumwa, A. O., Kibe, A. M., & Kipkemoi, J. N. (2022). Climate-Smart agriculture and potato production in Kenya: Review of the determinants of practice. *Climate and Development*, 14(1), 75–90. https://doi.org/10.1080/17565529.2021.1885336

Wang, L. Y. K., Lew, S. L., Lau, S. H., & Leow, M. C. (2019). Usability factors predicting continuance of intention to use cloud e-learning application. *Heliyon*, 5(6), e01788. https://doi.org/10.1016/j.heliyon.2019.e01788

Wekesa, B. M., Ayuya, O. I., & Lagat, J. K. (2018). Effect of climate-smart agricultural practices on household food security in smallholder production systems: Micro-level evidence from Kenya. *Agriculture and Food Security*, 7, 80. https://doi.org/10.1186/s40066-018-0230-0

Wu B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, 67, 221–232. https://doi.org/10.1016/j.chb.2016.10.028

Wut, T. M., Lee, S. W., & Xu, J. (2022). How do facilitating conditions influence student-to-student interaction within an online learning platform? A new typology of the serial mediation model. *Education Sciences*, 12(5), 337. https://doi.org/10.3390/educsci12050337

Yaseen, A., Bryceson, K., & Mungai, A. N. (2018). Commercialization behaviour in production agriculture: The overlooked role of market orientation. *Journal of Agribusiness in Developing and Emerging Economies*, 8(3), 579-602. https://doi.org/10.1108/JADEE-07-2017-0072

Zhu, D. H., & Chang, Y. P. (2014). Investigating consumer attitude and intention toward free trials of technology-based services. *Computers in Human Behavior*, 30, 328–334. https://doi.org/10.1016/j.chb.2013.09.008

Authors' Note

Authors acknowledge the Universiti Teknologi MARA for funding under the Geran Penyelidikan Dana Dalam Negeri (DDN) – Dana Lestari Khas Fasa 3 (600-TNCPI 5/3/DDN (06) (014/2021).

All correspondence should be addressed to
Noor Hadzlida Ayob
Faculty of Human Sciences
Universiti Pendidikan Sultan Idris
35900 Tanjong Malim, Perak, Malaysia
hadzlida@fsk.upsi.edu.my

Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu Volume 20(1), May 2024, 93-113

USING THE UTAUT2 COMPONENTS AND TRUST TO PREDICT CONSUMER ACCEPTANCE OF SMART HOME TECHNOLOGY: A SYSTEMATIC REVIEW

Nejc Plohl
University of Maribor
Slovenia
ORCID 0000-0001-9936-4039

Nenad Čuš Babič
University of Maribor
Slovenia
ORCID 0000-0002-3580-2068

Abstract: *While sales of smart home technology are increasing, some are still hesitant to use such products. These differences in smart home technology acceptance could potentially be explained with the extended Unified theory of acceptance and use of technology (UTAUT2). However, the explanatory power of UTAUT2 in this context is still relatively unclear, and additional extensions, such as the inclusion of trust, have been proposed recently. In this systematic review, we address this issue by synthetizing evidence from 32 articles dealing with the relationship between the UTAUT2 components, trust, and smart home technology acceptance. Our results reveal that the UTAUT2 components and trust are all consistently correlated with behavioral intentions. In contrast, multivariate results show that only performance expectancy, hedonic motivation, and price value are consistent predictors of technology acceptance. In the discussion, we outline possible explanations for such results and highlight the limitations of our review..*

Keywords: *smart home technology, acceptance, unified theory of acceptance and use of technology 2, trust, review.*

DOI: https://doi.org/10.14254/1795-6889.2024.20-1.5

INTRODUCTION

Many years have passed since the introduction of smart home technology (Richard Harper, 2003), with each year bringing new and unprecedented technological advances. Nowadays, smart home technology encapsulates numerous smart home devices (e.g., smart thermostats, smart lighting, and domestic robots) that can serve many different functions and thus lead to various health-related (e.g., detection of life-threatening events), environmental (e.g., reduction of energy consumption), financial (e.g., reduction of costs) and psychosocial benefits (e.g., decreased feelings of isolation; (Marikyan et al., 2019). While recent statistics show that sales of smart home devices are proliferating worldwide (Strategy Analytics, 2019), suggesting that individuals increasingly recognize the potential of smart home devices to contribute positively to their well-being, some are still reluctant to use the technology (Clutch, 2019). In fact, another recent survey of more than 2,000 households suggests that most people are still not interested in buying smart home devices at all (PricewaterhouseCoopers, 2016).

Several variables and broader theories have been considered to explain the diverse reactions of the general public, with one of the most recent and comprehensive theories being the extended Unified theory of acceptance and use of technology (UTAUT2; Venkatesh et al., 2012). This theory includes seven predictors that could explain considerable variance in the acceptance of smart home technology – performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. However, it could potentially benefit from another extension. Considering that even owners of smart homes have security/privacy concerns (YouGov, 2018) and that only a minority of consumers perceive smart home technology as trustworthy and safe (Accenture, 2019), special attention may need to be paid to factors such as trust that could mitigate security/privacy concerns and thus explain variance above and beyond the UTAUT2 model.

While both - the UTAUT2 model and trust - are increasingly being studied in the context of smart home technology, the literature has so far not exceeded the level of individual studies. The objective of this review is hence to conduct a systematic search of the relevant literature and synthesize the available evidence on the relationship between these (potential) predictors and acceptance of smart home technology.

Smart Home Technology

There are various definitions of smart home technology that can be categorized into two groups – definitions that focus on the nature of smart homes and definitions that are more service/context-oriented (Marikyan et al., 2019). One of the earliest and most influential definitions covering the nature of smart homes is that of Aldrich (2003), who defined smart homes as residences equipped with computing and information technology that address the needs of the occupants by providing comfort, convenience, security, and entertainment through the management of technology within the home and connections to the outside world. On the other hand, service/context-oriented definitions tend to be less broad and emphasize the specific benefits and uses of smart home technology. One such example is the definition proposed by Reinisch and colleagues (2011), which focuses on energy consumption. According to these authors, intelligent houses are equipped with several cooperating devices that constitute a homogeneous system that monitors electronic appliances and promotes efficient energy management and sustainability.

A recent literature review (Marikyan et al., 2019) suggests that different definitions overlap. Specifically, they generally emphasize three characteristics of smart homes, namely: technology (i.e., hardware and software components, including sensors, that are interconnected, integrated into home appliances and can detect changes in human behavior and other stimuli), services (e.g., remote controlling of household appliances, managing energy use, supporting and assisting users in their daily routine, anticipating and responding to users' needs), and the ability to satisfy users' needs (e.g., cost-efficiency, comfort, emotional needs, security, healthcare needs, quality of life, sustainability). These common components of definitions can be integrated into a comprehensive definition, which will guide the present systematic review: "*The smart home represents smart devices and sensors that are integrated into an intelligent system, offering management, monitoring, support, and responsive services and embracing a range of economic, social, health-related, emotional, sustainability and security benefits*" [Marikyan et al., 2019, pp. 144]. It is worth noting, however, that some authors still point to the presence of definitional confusion over what counts as smart home technology (Sovacool & Furszyfer Del Rio, 2020).

The Unified Theory of Acceptance and use of Technology-2

Numerous theoretical models have been developed to explain the acceptance and use of information technology, most notably the Technology acceptance model (TAM; Davis, 1989), the Unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003), and most recently, the extended Unified theory of acceptance and use of technology-2 (UTAUT2; Venkatesh et al., 2012). While all of these models apply to information technology in the broadest sense, they all have their place in the specific context of smart home technology as well.

First, the UTAUT2 incorporates all four UTAUT constructs (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions) that influence behavioral intentions to use technology and actual technology use. *Performance expectancy* refers to the degree to which using technology will provide benefits to consumers in performing certain activities; *effort expectancy* refers to the level of ease associated with consumers' use of technology; *social influence* refers to the extent to which consumers perceive that important others believe they should use a particular technology; and *facilitating conditions* refer to consumers' perceptions of the resources and support available to use technology (Brown & Venkatesh, 2005; Venkatesh et al., 2003, 2012). Per the UTAUT model, the first three constructs predict behavioral intentions to use technology, and the intentions, together with facilitating conditions, predict the use of technology (Venkatesh et al., 2012).

Second, the UTAUT2 extends the UTAUT model by transferring it from organizational contexts (where it first originated) to the context of consumer use and by adding three additional constructs (i.e., hedonic motivation, price value, and habit). *Hedonic motivation* refers to the fun or pleasure derived from using technology (Brown & Venkatesh, 2005; Venkatesh et al., 2012); *price value* refers to consumers' cognitive tradeoff between the perceived benefits of using technology and the monetary cost associated with technology use

(Dodds et al., 1991; Venkatesh et al., 2012); and *habit* refers to the extent to which an individual believes the technology use behavior to be automatic (Limayem et al., 2007; Venkatesh et al., 2012). The UTAUT2 model suggests that hedonic motivation and price value predict behavioral intentions, while habit predicts both behavioral intentions and technology use (Venkatesh et al., 2012).

The UTAUT2 offers a comprehensive and integrative approach (by incorporating the main explanatory variables of previous theoretical models on technology acceptance and use) and hence represents one of the dominant theoretical frameworks in this area of research (as shown by the sheer number of citations). Additionally, the model has proven to be valuable when examining the acceptance and use of technology in various contexts (Herrero et al., 2017; Tamilmani et al., 2020). For example, a recent meta-analysis incorporating the results of 60 studies has shown that the proposed UTAUT2 factors correlate with behavioral intentions and technology use in a hypothesized way, with the strongest zero-order correlates and predictors of behavioral intentions to use technology being habit (r = .64, β = .27), performance expectancy (r = .62, β = .25) and hedonic motivation (r = .58, β = .25; Tamilmani et al., 2020).

Trust as an Additional Predictor of Technology Acceptance

Although the UTAUT2 is already an extension of earlier models and theories of technology acceptance, researchers often extend the UTAUT2 model even further by including additional variables such as trust, perceived risk, self-efficacy, attitudes, and personal innovativeness. Among these variables, trust is the one that is most commonly added to the UTAUT2, with studies generally showing that it is a significant predictor of behavioral intentions to use technology and actual technology use (Tamilmani et al., 2020). Trust has also been proposed as an important extension of the UTAUT2 in the specific context of smart consumer products and smart homes, as the lack of consumer trust in such products likely hampers their use diffusion and potential benefits (Michler et al., 2019). For example, Shuhaiber and Mashal (2019) argue that trust (together with awareness and perceived enjoyment) is an important personal factor that needs to be considered when predicting intentions to use smart home technology.

In general, trust can be defined as the intention to accept potential vulnerability based on positive expectations about a person or an institution (Dirks & Ferrin, 2002) or as the belief that the other party will behave in a socially responsible manner and meet the expectations of the trusting party without exploiting their vulnerability (Gefen, 2000; Mayer et al., 1995). Similarly to other areas of research (e.g., consumers' acceptance of e-commerce; Pavlou, 2003), we argue that consumers' trust in smart home technology could thus be a key element in helping consumers overcome risk concerns and reduce the uncertainty facing the adoption of smart homes (Shuhaiber & Mashal, 2019).

Aims of the Review

In this paper, we present a systematic literature review that synthesizes the available evidence on the relationship between the UTAUT2 components (i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit) as well as trust on one hand and consumer acceptance of smart home technology (i.e., intentions to use smart home technology, use of smart home technology) on the other. The hypothesized relationships considered in the review are depicted with regular lines in Figure 1 below. The dashed lines indicate relationships initially searched for but not examined in this review due to the low number of research articles.

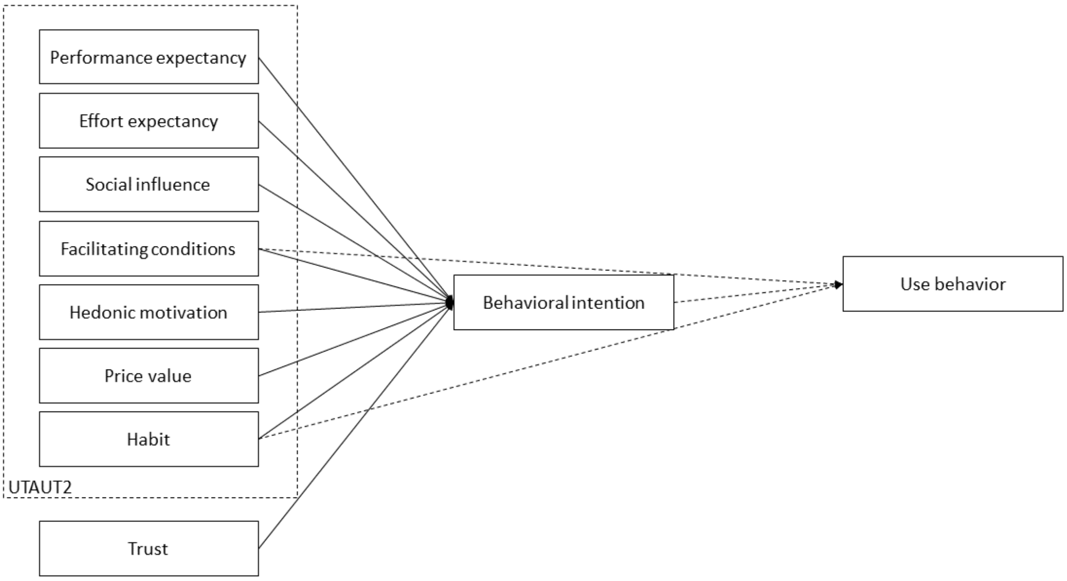

Figure 1. UTAUT2 factors and Trust as Predictors of Behavioral Intentions.

METHODS

This systematic literature review is guided by the Cochrane method, and the search method and findings are presented in accordance with the relevant sections of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Higgins & Green, 2008; Moher et al., 2009). The protocol used to conduct this review is described in detail in the following paragraphs.

Eligibility Criteria

In order to be considered for inclusion in the systematic literature review, the studies had to 1) be classified as articles or conference proceedings (as opposed to, for example, reviews), 2) be available in English, and 3) be fully published (i.e., preprints and other unpublished articles were not considered). Studies were then excluded from the present review if: 1) they were not empirical (i.e., no quantitative evidence obtained by collecting data on human subjects), 2) they did not address consumer acceptance but other forms of acceptance instead (e.g., in the organizational context), 3) the technology in focus did not fit our definition of smart homes, 4) they did not report on at least one relationship from Figure 1, and 5) we were unable to access the full text of the article. In cases where the entry was not a duplicate per se, but the authors reported identical results, only one version was included in the review. In a similar vein to other systematic reviews and meta-analyses that focused on UTAUT2 factors (Taiwo & Downe, 2013), the included studies had to involve empirical testing of UTAUT2 directly or indirectly using the same operationalized constructs as the original model (i.e., same name, a direct reference to UTAUT2 in the definition of the construct or use of previous UTAUT2 questionnaires).

Information Sources and Search Strategy

Two databases, which complement each other well, SCOPUS and Web of Science (Burnham, 2006), were used to identify the relevant articles. The main search was carried out on September 1st, 2022, using a search strategy that combined different *predictors of interest*, indicators of *acceptance*, and *smart home technology*. The terms later combined into a nested format and searched for in titles, abstracts, and keywords are shown in Table 1 below. In particular, terms within the same block were combined using the OR operator, and different blocks were combined using the AND operator. In order to identify potential additional articles, different combinations of search terms were also run in Google Scholar, as the use of Google Scholar can lead to the identification of additional unique entries (Martín-Martín et al., 2018). In Google Scholar, we also used the cited reference search for the article by Venkatesh and colleagues (Venkatesh et al., 2012) and were particularly focused on identifying articles specifically related to smart home technology.

Table 1. The Terms Derived From the Concepts

Predictors	Acceptance	Smart homes
"performance expectancy"	accept*	"smart home?"
"effort expectancy"	adopt*	"smart house?"
"social influence?"	intention*	"home automation"
"facilitating condition?"	"use behavior?r"	"smart building*"
utaut	use	
"hedonic motivation"		
"price value"		
habit?		
utaut2		
utaut-2		
trust		

Study Selection

The search strategy described above was applied to both databases, and the identified records were downloaded and merged into a single Microsoft Excel spreadsheet. Duplicate articles (i.e., those identified by the search strategy in both databases) were eliminated. Additional articles (i.e., those not yet identified by the search strategy in Scopus and Web of Science) were also added to the same spreadsheet. In the next step, the titles and abstracts of the records were carefully screened. Those articles deemed ineligible (based on their title or abstract) were excluded, and the remaining articles, specifically those deemed eligible and those that did not contain enough information for a decision to be made, were again screened based on the full text of the article. Eligible articles were included in the final review. Ineligible articles were formally excluded (with reasons for exclusion noted).

Data Collection

A data extraction table was created to aid the synthesis of the eligible studies. The table included publication characteristics of the articles (authors, year, country), sample characteristics (number of participants, whether the participants belonged to any specific groups, age, gender, experience with smart home devices), the instruments used to measure the predictors and their internal consistency (Cronbach's α), the instruments used to measure indicators of technology acceptance and their internal consistency (Cronbach's α), whether the study referred to smart home technology in general or any specific category of smart home devices, the main findings of the studies (univariate and multivariate statistical results expressed by correlation coefficients and path/regression coefficients), and an extra column for notes.

RESULTS

Study Selection

The main and additional searches yielded a total of 226 unique articles. After the titles and abstracts were screened, 68 articles (30.1%) still fit the criteria. Of these, 32 articles (14.2%) met the inclusion criteria and were hence included in the final synthesis. As some articles include several studies, the final number of studies is higher (n = 36). The specifics of the search selection process are outlined in Figure 2 below.

Study Characteristics

As can be seen in Table 2, all included articles have been published since 2010, and a majority (84.4%) have been published in the last five years, indicating a sharp increase of research articles in this area. Most of the articles (93.8%) were published in JCR/Scopus-indexed journals and conference proceedings. Studies were conducted on participants with different cultural backgrounds; in particular, twelve studies (33.3%) were conducted in European countries, eleven studies (30.6%) in Asian countries, nine studies (25.0%) in the United States, two studies in Australia (5.6%), and one study in South America (2.8%). Moreover, one study (2.8%) combined samples from both Europe and Asia. The minimum sample size among the included studies was 53 and the maximum 1226, with the average study including 386.11 (SD = 304.25) participants. Most of the studies (69.4%) used general population samples, and the rest were performed on aging adults (22.2%) or student participants (8.3%). All studies that report data regarding gender used mixed-gender samples (88.9% of all included studies), and the studies differed substantially in whether the participants had any prior experience (although such data were often missing).

In most cases, the authors did not use the entire UTAUT2 model in their research but rather focused on a limited number of UTAUT2 factors while simultaneously adding other variables into the model. The most studied UTAUT2 factors are those appearing in the initial UTAUT model (Venkatesh et al., 2003) – performance expectancy with 28 studies, effort expectancy with 25 studies, social influence with 24 studies, and facilitating conditions with 18 studies. Among the variables that first appeared in the UTAUT2 model (Venkatesh et al., 2012), the most frequently examined variables are price value (14 studies) and hedonic motivation (13 studies), followed by habit (7 studies). The additional predictor included in this review, trust, was explored in 14 studies. As for the dependent variables, the studies focused almost exclusively on behavioral intentions (i.e., intentions to adopt/accept smart home technology). In fact, as only a few studies included in the synthesis also reported associations between predictors of interest and actual use behavior, such relationships are not considered in the present systematic review.

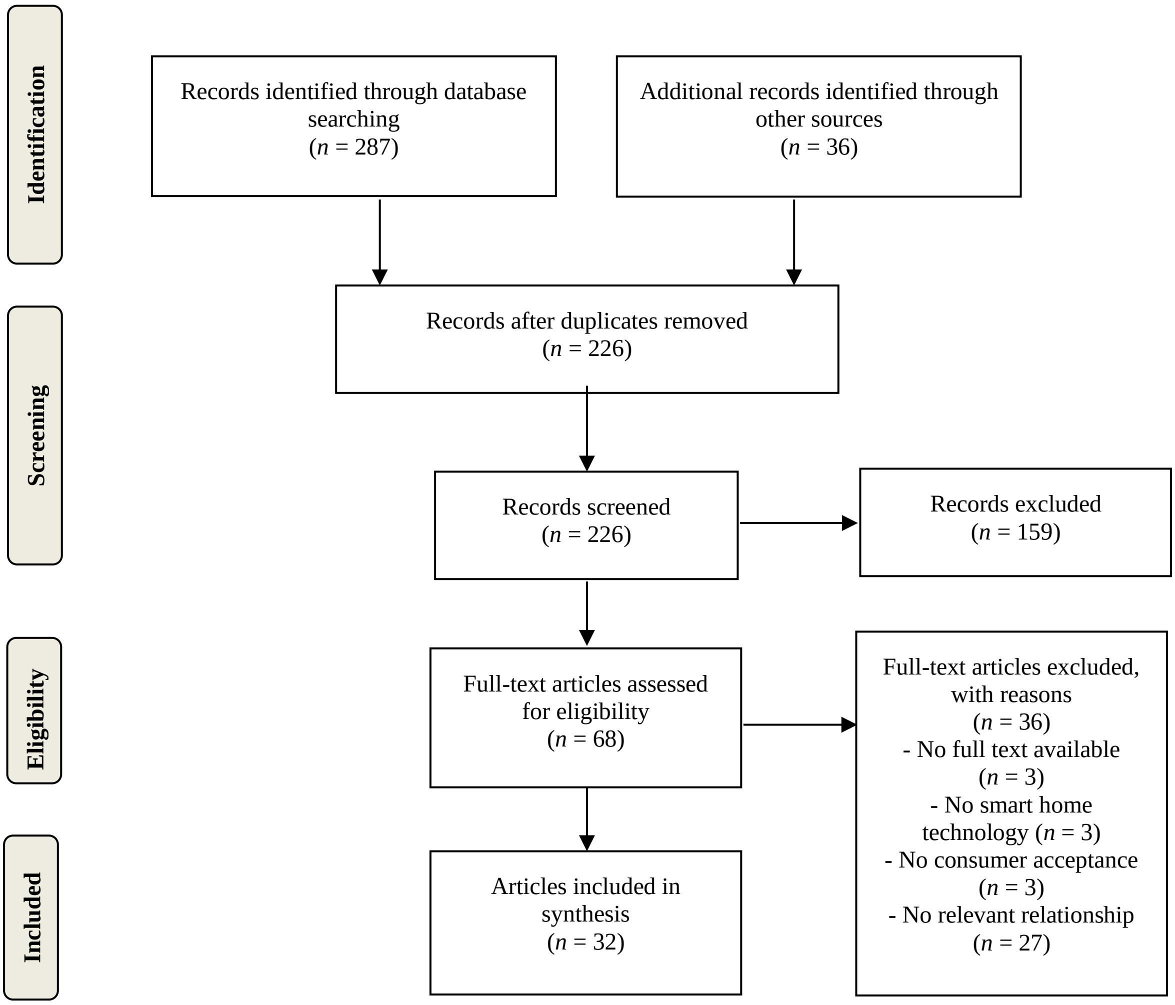

Figure 2. PRISMA Flowchart Depicting the Study Selection Process

In terms of the scales used, there seems to be no clear consensus; various scales - often self-construed or considerably adapted from previous scales, especially the one by Venkatesh and colleagues (2003, 2012) - were used to measure the constructs of interest. The internal reliability of the scales that were employed was, when reported, generally sufficient (Cronbach's $\alpha \geq .70$), except for the scales used to measure social influence in one of the included studies (Gumz et al., 2022) and facilitating conditions in two of the included studies (Baudier et al., 2020; Heerink et al., 2010). Lastly, considering the types of smart home devices included in the review, the largest share of studies (38.9%) investigated smart home devices in general, followed by studies focusing on energy management smart home devices (25.0%; e.g., smart thermostats, smart lighting, energy management services), health-related smart home devices (16.7%; e.g., smart healthcare, telehealth), and smart speakers and voice-based digital assistants (13.9%). The remaining studies (5.6%) examined assistive robots, screen agent technology, and smart interactive home textiles. A detailed table with study characteristics can be found in the Appendix.

Table 2. A List of All Included Articles.

#	Authors	Year	#	Authors	Year
1	Heerink et al.	2010	17	Chen et al.	2020
2	Kohnke et al.	2014	18	Mamonov & Koufaris	2020
3	Ahn et al.	2016	19	McCloskey & Bennet	2020
4	Cimperman et al.	2016	20	Wang et al.	2020
5	Moon & Hwang	2016	21	Alkawsi et al.	2021
6	Brauner et al.	2017	22	Andini & Adiwijaya	2021
7	Chen et al.	2017	23	Canziani & MacSween	2021
8	Aldossari & Sidorova	2018	24	Oyinlola Ayodimeji et al.	2021
9	Pal et al.	2018	25	Shanthana Lakshmi & Gupta	2021
10	Etemad-Sajadi & Gomes dos Santos	2019	26	Vimalkumar et al.	2021
11	Gu et al.	2019	27	Zaharia & Würfel	2021
12	Juric & Lindenmeier	2019	28	Grosse-Kreul	2022
13	Mashal & Shuhaiber	2019	29	Gumz et al.	2022
14	Nikou	2019	30	Maswadi et al.	2022
15	Shuhaiber & Mashal	2019	31	Meyer-Waarden et al.	2022
16	Baudier et al.	2020	32	Sorwar et al.	2022

Major Findings

Performance Expectancy

Twenty-eight studies explored the relationship between performance expectancy (PE) and the intention to accept smart home technology. Among these studies, seventeen report correlational data, with results clearly and consistently showing that PE is significantly correlated with behavioral intentions, regardless of the sample characteristics, the measure used, and the type of smart home devices. While the strength of the correlations varies to some extent, fourteen (82.4%) studies indicate a strong (and positive) correlation ($r \geq .50$).

PE was used as a direct predictor of behavioral intentions in twenty-three studies measuring these two variables. In a similar vein to correlational data, PE generally emerged as a significant predictor of behavioral intentions despite appearing in regression/structural models that included a wide array of additional predictors. Among the studies in our review, only three (13.0%) found that PE was not a significant predictor of the intention to use this technology. Two of these studies were conducted in the context of smart meters and one in the context of smart interactive home textiles. Overall, the regression/path coefficients varied considerably in the included studies, with most (43.5%) reporting strong β coefficients (≥ .30).

Effort Expectancy

Twenty-five studies investigated the relationship between effort expectancy (EE) and the intention to accept smart home technology, but only sixteen of these studies report correlational data. The results of these studies are highly consistent, with all studies but one showing that EE is significantly correlated with behavioral intentions. The one study that stands out in terms of its findings is the study by Kohnke and colleagues (2014), in which the acceptance of telehealth equipment was investigated on the sample of elderly patients, clinicians, and agency leadership personnel (it should be noted that group membership was not a significant predictor of behavioral intentions). Overall, the strength of the correlations varied substantially between the studies, with eight studies (50.0%) showing strong associations between the variables, four studies (25.0%) showing intermediate associations ($.30 < r < .50$) and four studies (25.0%) showing weak associations ($r \leq .30$).

Furthermore, eighteen studies examined the hypothesis that EE is a direct predictor of the intention to accept smart home technology. Slightly more than half of the studies (55.6%) found that EE is not a unique predictor of behavioral intentions when included in the regression/structural model together with other UTAUT2 factors and/or other variables. On the other hand, eight studies (44.4%) report that EE significantly predicts behavioral intentions, but only seven found a significant relationship in the expected direction (the study by Andini and Adiwijaya, 2021, surprisingly found that higher perceived effort needed to use technology increases behavioral intentions). Although the seven studies reporting significant findings in the expected direction are based on different sample sizes and participants from different countries, four were conducted on older participants (the remaining were conducted on general samples and students). Overall, studies reporting regression/path coefficients mostly show weak β coefficients ($\beta \leq .15$).

Social Influence

Twenty-four studies considered social influence (SI) as a correlate and/or predictor of the intention to adopt smart home technology. Sixteen of these studies provide correlational data. Their results consistently show that, regardless of different sample and study characteristics, SI is significantly correlated with the intention to accept smart home technology. While the strength of the correlations varies, the majority of correlation coefficients (62.5%) indicate a strong relationship ($r \geq .50$) between the variables.

Twenty studies also examined whether SI is a direct predictor of behavioral intentions in multivariate models. In the case of regression/structural equation modeling analyses, the results are somewhat mixed; eleven studies (55.0%) suggest that SI is a unique predictor of the intention to accept smart home technology, while nine (45.0%) studies suggest that SI is not a significant predictor of behavioral intentions when other variables are included in the regression/structural model. The studies that do not report significant regression/path coefficients differ in many aspects, but a relatively common denominator is that six out of nine studies used older samples. Overall, the majority (45.0%) of studies only found a weak predictive value of SI.

Facilitating Conditions

Eighteen studies explored the relationship between facilitating conditions (FC) and the acceptance of smart home devices. Within this array of research articles, thirteen studies reported correlational data. These studies almost unanimously show that FC are a significant correlate of intentions to accept smart home technology. The only exception is the study by

Kohnke and colleagues (2014), which investigated the acceptance of telehealth equipment on a sample of elderly patients, clinicians, and agency leadership personnel. Overall, six studies (46.2%) imply a strong relationship between FC and behavioral intentions, five studies (38.5%) imply an intermediate relationship, and two studies (15.4%) a weak relationship between these two variables.

FC were used as a direct predictor of behavioral intentions in twelve studies. The results of these studies predominantly show that facilitating conditions are not a significant predictor of intentions to accept smart home devices. In fact, only four studies (33.3%) found FC to be a significant predictor of smart home acceptance. Two of the studies (Ahn et al., 2016; Cimperman et al., 2016) that show significant results were carried out on samples consisting exclusively or predominantly of older participants, while the remaining two studies (Alkawsi et al., 2021; Vimalkumar et al., 2021) were conducted among the general population. Moreover, two of these studies investigated the acceptance of energy management smart home devices, while the remaining two studied health-related smart home technology and voice-based smart home technology. Additionally, in most studies (66.7%), the regression/path coefficients point to a weak association between the variables.

Hedonic Motivation

Thirteen studies investigated the relationship between hedonic motivation (HM) and behavioral intentions. Seven of them report correlational data, with the results consistently showing that HM correlates significantly with behavioral intentions related to the acceptance of smart home technology. Whereas correlation coefficients spanned from intermediate to strong, the majority of the studies (85.7%) showed values that can be described as strong.

Additionally, twelve studies tested whether HM directly predicts the intention to accept smart home technology. Most of these studies (75.0%) report significant regression/path coefficients, suggesting that HM is a unique predictor of behavioral intentions when other variables are entered into the model. It is worth noting that the three studies that did not find HM to be a significant predictor (Baudier et al., 2020; Grosse et al., 2022; McCloskey et al., 2020) were all conducted in western countries (France, United States, Germany), but tackled different smart home technologies (energy management, smart speakers, general). They also employed different samples (two were based on general samples and one on students). Overall, the regression/path coefficients varied in the included studies, but the largest share of studies (55.6%) reports a strong association between HM and smart home acceptance.

Price Value

Fourteen studies considered price value (PV) as a correlate and/or predictor of the intention to adopt smart home technology. Ten of these studies provide correlational data, and the results highly consistently (90.0%) show that PV correlates significantly with behavioral intentions. The only exception is the study by Nikou (2019), which was conducted in the context of general smart home technology. Overall, the power of correlation coefficients ranged from weak to strong, with the same percentage (40.0%) of studies suggesting a weak and intermediate association, while only 20.0% of studies yielded strong correlation coefficients between PV and behavioral intention.

Twelve studies additionally tested multivariate regression/structural models with PV included as a direct predictor of behavioral intentions. The results predominantly (75.0%) show that PV uniquely predicts the intention to accept smart home technology (in the expected direction). The remaining three studies, however, did not find PV to be a significant predictor of behavioral intentions when other variables are entered into the model. All studies (Baudier et al., 2020; Chen et al., 2017; Mamonov & Koufaris, 2020) that do not report significant results were conducted in western countries (USA, France) on participants who were, on average, relatively young and without any prior experience with smart home technology. In terms of the content, they were either concerned with smart meters/thermostats (Chen et al., 2017; Mamonov & Koufaris, 2020) or smart home objects in general (Baudier et al., 2020). As for the strength of path/regression coefficients, most studies (66.7%) report weak associations between variables of interest.

Habit

Seven studies examined the relationship between habit (HA) and behavioral intentions in the context of smart home technology acceptance. All seven studies report correlational data, with their results consistently showing that HA correlates significantly with intentions to accept smart home technology. However, the strength of the association varied considerably between the studies, with five studies (71.4%) showing a strong association and two studies (28.6%) showing a weak association.

All seven studies also report multivariate data, with the predominant conclusion being that HA is a significant predictor of smart home acceptance. The two non-significant results both stem from the study by Chen and colleagues (2020), which was conducted on two separate samples (American and Japanese participants with no prior experience) and investigated the role of different factors in predicting the adoption of home energy management systems. Overall, the β coefficients ranged from strong (57.1%) to weak (42.9%). It is worth noting that the conceptualization of HA differed between the studies. This is further discussed in the next section.

Trust

Fourteen studies investigated the relationship between trust (TR) and the intention to accept smart home technology. Twelve of them report correlational data that capture the association between the two variables. The results of these studies are very consistent, as they all concluded that TR and acceptance of smart home technology are significantly correlated. The strength of the correlation coefficients varied from weak to strong, with the largest share of studies (41.7%) concluding that trust is strongly associated with behavioral intentions.

Eleven studies have also investigated the possibility of TR being a unique predictor of behavioral intentions. Among these studies, more than half (54.3%) report that TR is indeed a significant predictor of intentions to accept smart home technology, but the relationship is negative in one case. The remaining five studies did not find TR to be a significant predictor of behavioral intentions. All studies that did not report a significant role of TR (Chen et al., 2020; Etemad-Sajadi & Gomes Dos Santos, 2019; Heerink et al., 2010; Sorwar et al., 2022) were conducted on samples that were exclusively or predominantly older. The included studies differed considerably in the way they defined and operationalized trust, which is discussed in the next section. Overall, most studies (63.6%) found that the strength of association between trust and intention to accept smart home technology is intermediate in strength.

Table 3. Quantitative Synthesis Based on All Studies Included in the Review.

Predictor	***N***	**Univariate results (*r*)**						**Multivariate results (β)**					
		n	Sig	Weak	Intermediate	Strong	Str. unclear	*n*	Sig	Weak	Intermediate	Strong	Str. unclear
PE	28	17	17	1	2	14	0	23	20	3	9	10	1
EE	25	16	15	4	4	8	0	18	8[a]	7	4[a]	3	4
SI	24	16	16	1	5	10	0	20	11	9	7	4	0
FC	18	13	12	2	5	6	0	12	4	8	2	2	0
HM	13	7	7	0	1	6	0	12	9	4	3	5	0
PV	14	10	9	4	4	2	0	12	9	8	1	1	2
HA	7	7	7	2	0	5	0	7	5	3	0	4	0
TR	14	12	12	3	4	5	0	11	6[a]	4	7[a]	0	0

Notes. Sig indicates the number of studies that showed significant results. Univariate results criteria: weak ($r \leq .30$), intermediate ($.30 < r < .50$), strong ($r \geq .50$). Multivariate results criteria: weak ($\beta \leq .15$), intermediate ($.15 < \beta < .30$), strong ($\beta \geq .30$). [a] One study showed results in an unexpected direction (different valence).

DISCUSSION

The present study aimed to systematically review the existing research articles that investigated the relationship between the UTAUT2 components and trust on the one hand and the acceptance of smart home technology on the other. The majority of studies found that all UTAUT2 components are significantly correlated with the acceptance of smart home technology. However, the strength of the associations differed considerably between the components, with performance expectancy, social influence, facilitating conditions, hedonic motivation, and habit standing out as the strongest correlates of smart home technology acceptance. These results are relatively in line with a broader meta-analysis of UTAUT2, which has also concluded that the components of UTAUT2 are generally significantly correlated with behavioral intentions, and identified habit, performance expectancy, and hedonic motivation as the strongest correlates of behavioral intentions (Tamilmani et al., 2020). However, there is some discrepancy regarding the role of social influence and facilitating conditions; these variables emerged as one of the strongest correlates of behavioral intentions in our review but were found to be one of the weakest UTAUT2 correlates of behavioral intentions in the meta-analysis conducted by Tamilmani and colleagues (2020). The observed difference could potentially be attributed to the fact that the smart home technology market is still at a relatively early stage, in which many potential users lack enough knowledge to rely solely on their own skills and make an independent decision about using it. As such, they might be particularly prone to basing their decisions on the opinions or suggestions of others and looking for other resources and support available (Yang et al., 2016).

Furthermore, the present review also reveals that trust is a consistently significant correlate of behavioral intentions. This finding is new; while previous reviews and meta-analyses have identified trust as one of the most common extensions of UTAUT2 (Tamilmani et al., 2020), to our knowledge, no review has explicitly addressed this relationship. Such results support the notion that consumers who trust smart home technology (or the utilities behind it) are also more likely to accept it. A closer examination, however, reveals considerable variance in the strength of the associations, which could be a result of different definitions of this construct. Weak associations were primarily found in studies that focused on trust in utility companies, which defined trust as, for example, "*the extent that home energy management system users believe utilities or energy providers are honest, dependable, and can reliably provide quality services*" (Chen et al., 2020, pp. 4). In contrast, strong associations were primarily found in studies that focused on trust in *technology* rather than the utilities behind the technology, with a common element of such definitions being the security aspect (e.g., Pal et al., 2018).

When it comes to the predictive role of UTAUT2 components and trust, the results are less uniform and clear; only performance expectancy stands out as a highly consistent predictor of behavioral intentions, followed by hedonic motivation and price value that emerged as significant predictors of smart home technology acceptance in 75% of the included studies. First, the proportion of significant multivariate results in our review is lower compared to the results of the recent general meta-analysis on UTAUT2 (Tamilmani et al., 2020); more precisely, Tamilmani and colleagues (2020) report that the UTAUT2 components were significant predictors of behavioral intentions in 72.8% of all relevant cases, while a comparable statistic is at 60.9% in our study. This could be interpreted in several ways. Some of the UTAUT2 components might be less important in this specific context, which would suggest omitting such components (and perhaps replacing them with other variables that could explain a unique portion of the variance). In contrast, it is also possible that the models in this specific context often contain overlapping variables as predictors, making some of the UTAUT2 components seem redundant. Second, the strength of the regression coefficients was generally weak to intermediate, which is largely in line with previous findings in other contexts (Tamilmani et al., 2020). However, despite relatively low regression weights, coefficients of determination (R^2) for the full models, when available, were generally relatively high (mostly above .50). Third, when comparing the importance of different predictors, the context of smart home technology again seems to deviate slightly from information technology in general (although there are also several similarities, e.g., the important predictive role of performance expectancy and hedonic motivation). Notably, price value was among the weakest predictors of behavioral intentions in the meta-analysis (Tamilmani et al., 2020) but is among the more consistent predictors in our review set in the specific context of smart home technology. The particularly important role of price value observed in our systematic review may be attributed to the specific characteristics of the supporting studies (e.g., age; research generally shows high importance of price value among older people; Chen & Chan, 2011). It should be noted, however, that while price value was a relatively consistent predictor of behavioral intentions, it was still a weak predictor in most instances. Finally, trust was a significant predictor of behavioral intentions (in the predicted way) in only five of the eleven studies that examined this relationship, and the regression coefficients were weak to intermediate. As such, it is difficult to determine its unique importance when studying smart home technology acceptance and even more troublesome to make conclusions regarding the incremental value of trust (as an added component to the UTAUT2), especially since none of the individual studies used all UTAUT2 components as well as trust as predictors of technology acceptance. The role of trust hence remains somewhat ambiguous.

Taken together, while correlational results strongly support the notion that the UTAUT2 components and trust are important correlates of smart home technology acceptance, multivariate data provide more limited evidence; the only consistently significant predictors of technology acceptance in multivariate models are performance expectancy, hedonic motivation, and price value, and the regression weights for all included variables were mainly weak to intermediate. While such findings still provide evidence-based justification for the use of the UTAUT2 model (and trust), they also point to the possibility that the UTAUT2 is still not comprehensive enough and/or that some of the components included in this review are redundant because they do not explain unique variance in behavioral intentions to a high enough degree. It is hence possible that the UTAUT2 may indeed need another extension in the smart home context, but it could perhaps also use some reduction in this context (e.g., by removing effort expectancy and facilitating conditions from the models), at least when answering certain research questions among certain population subgroups.

Although the present study did not focus on the role of moderators proposed by the UTAUT2 (i.e., age, gender, experience) or other potential moderators, such data were collected, revealing some associations that could be further explored in future studies. With the exception of performance expectancy, all variables considered in this review showed considerable variability between the studies, indicating the presence of moderators that determine the strength of the association between predictor variables and the acceptance of smart home technology. Based on our findings, one of the more prominent moderators in the context of smart home technology could be age; its potential importance surfaced in the case of effort expectancy (a significant predictor of behavioral intentions especially in samples consisting of older participants), social influence (not significant especially in samples consisting of older participants), facilitating conditions (significant especially in samples consisting of older participants), price value (not significant especially in samples consisting of younger participants), and trust (not significant especially in samples consisting of older participants). Other potential moderating variables (gender, previous experience, country) had a more minor role in reviewed articles; for example, our observations imply that the relationship between price value and smart home technology acceptance is less important in Western countries, but this needs to be explored further in future research.

In addition to the potential moderators, the strength of the associations between constructs also varied depending on how the authors defined them. Differences in conceptualizations were particularly prominent in the case of habit and trust (and, to a certain extent, facilitating conditions). Different definitions of trust have already been presented above, whilst the studies that investigated habit (similarly to other contexts, the inclusion of habit in the smart home context is relatively rare; Tamilmani et al., 2019) sometimes deviated considerably from its original conceptualization, especially when respondents had no prior experience with smart homes. For example, some authors define it in a way that is very similar to behavioral intentions (Baudier et al., 2020; example item: "*The use of smart home* *objects could become a habit for me*"), or refer to other similar habits, not necessarily habits related to the use of smart home technology in focus (Chen et al., 2020).

LIMITATIONS AND FUTURE DIRECTIONS

The results of the present systematic review are limited both by the shortcomings of the included studies as well as by the limitations of our review.

First, none of the individual studies included in our review entered all the variables of interest into the same multivariate model. Instead, the authors often focused on only a handful of UTAUT2 variables (and/or trust). Furthermore, they often included additional variables not considered in this review (e.g., personal innovativeness, perceived security, and techno-coolness). It is, therefore, difficult to compare regression coefficients, the strength of which, by definition, varies based on other predictors that appear in multivariate models. This also makes it difficult to draw a clear conclusion about the potential value of expanding UTAUT2 with trust. Second, our conclusions are somewhat limited due to the different conceptualizations and operationalizations of the studied constructs. In other words, the same predictor variables were defined and measured in very different ways. The differences in definitions were particularly prominent with facilitating conditions, habit, and trust, while other constructs (such as performance expectancy, effort expectancy, hedonic motivation, and price value) were defined more uniformly but were given different names (such as perceived usefulness, perceived ease of use, perceived enjoyment, and cost concerns derived from TAM and other models). As such, it was sometimes difficult to demarcate constructs and decide whether the studied construct meets our inclusion criteria. To some extent, the field seems to suffer from the so-called jingle-jangle fallacy, which refers to the false assumptions that two different things are the same because they bear the same name or that two almost identical things are different because they are labeled differently (Kelley, 1927). This problem is aggravated by the fact that authors mainly use self-construed scales that fit their definitions and research questions or adapt existing scales (sometimes without adequate justification) instead of using previously validated scales. While the reliability of self-construed scales was generally high enough when reported, the validity of such scales is not always self-evident. Third, while the included studies were mostly conducted on large samples (although this varies quite a lot between the studies), demographic data such as age (with a mean and standard deviation) and previous experience with smart home technology are often not reported thoroughly enough. While this does not necessarily affect our findings, it could be a critical limitation for future systematic theoretical reviews or meta-analyses focusing on the moderators of the relationship between UTAUT2 components, trust, and smart home technology acceptance. Finally, it is also noteworthy that some of the included variables (e.g., habit) have only been investigated in a few studies.

Moreover, the present systematic review is to some extent limited by our relatively dispersed focus; as we aimed to answer our research questions quite broadly, referring to smart home technology in general, our search strategy did not include any specific types of smart home technology or specific smart home technology products. Therefore, it is possible that some of the potentially relevant articles were overlooked. This could be addressed in the future by employing a more narrow and detailed focus. Furthermore, besides the already mentioned lack of systematic attention to moderators in the present review, studying mediators could also be useful to deepen our understanding of what drives the association between variables. In fact, it is possible that some of the variables considered in this review, in particular trust, may have a different role in models predicting the acceptance of smart home technology (e.g., trust as an indirect predictor instead of a direct one). This should be explored in the future. Finally, the present review lacks a proper quality assessment of the included studies. Such insights could help us further assess the validity of the findings obtained in individual studies and the validity of the derived synthesis.

CONCLUSIONS

This is the first systematic review that examined the relationship between the UTAUT2 components and their possible extension, trust, in the specific context of smart home technology. The evidence suggests that all included variables correlate with behavioral intentions to accept smart home technology. However, the multivariate results reveal that only performance expectancy, hedonic motivation, and price value are consistent, unique predictors of smart home technology acceptance across studies. Taken together, our findings thus illuminate the fact that the UTAUT2 and its' components should not be seen as the perfect and final recipe for explaining the different responses of the general public. Instead, it is likely that additional variables, such as more general psychological variables as opposed to variables specific to the technology at hand, will also need to be considered in the future. In a similar vein, it is likely that not all UTAUT2 components are needed to explain technology acceptance in the specific context of smart home technology. However, given the relatively small number of articles, their limitations, and other shortcomings of the review, this interpretation should be considered with caution.

REFERENCES

Accenture. (2019). *Consumer perceptions of smart home technology use worldwide as of 2019*. Statista. https://www-statista-com.ezproxy.lib.ukm.si/statistics/1075518/smart-home-technology-consumer-perception-worldwide/

Ahn, M., Kang, J., & Hustvedt, G. (2016). A model of sustainable household technology acceptance. *International Journal of Consumer Studies*, *40*(1), 83–91. https://doi.org/10.1111/ijcs.12217

Aldossari, M. Q., & Sidorova, A. (2018). Consumer acceptance of internet of things (IoT): Smart home context. *Journal of Computer Information Systems*, 1–11. https://doi.org/10.1080/08874417.2018.1543000

Aldrich, F. (2003). Smart homes: Past, present and future. In R Harper (Ed.), *Inside the smart home* (pp. 17–39). Springer. https://doi.org/10.1007/1-85233-854-7

Alkawsi, G. A., Ali, N., Mustafa, A. S., Baashar, Y., Alhussian, H., Alkahtani, A., Tiong, S. K., & Ekanayake, J. (2021). A hybrid SEM-neural network method for identifying acceptance factors of the smart meters in Malaysia: Challenges perspective. *Alexandria Engineering Journal*, *60*(1), 227–240. https://doi.org/10.1016/j.aej.2020.07.002

Andini, N. D., & Adiwijaya, K. (2021). What factors do affect the adoption of internet of things (smart home) in Indonesia. *International Journal of Business and Technology Management*, *3*(2), 84–97.

Baudier, P., Ammi, C., & Deboeuf-Rouchon, M. (2020). Smart home: Highly-educated students' acceptance. *Technological Forecasting and Social Change*, *153*, 119355. https://doi.org/10.1016/j.techfore.2018.06.043

Brauner, P., Van Heek, J., & Ziefle, M. (2017). Age, gender, and technology attitude as factors for acceptance of smart interactive textiles in home environments: Towards a smart textile technology acceptance model. In *ICT4AWE 2017 - Proceedings of the 3rd International Conference on Information and Communication Technologies for Ageing Well and e-Health*, (pp. 13–24). Springer Cham.

Brown, S. A., & Venkatesh, V. (2005). Model of adoption of technology in households: A baseline model test and extension incorporating household life cycle. *MIS Quarterly: Management Information Systems*, *29*(3), 399–426. https://doi.org/10.2307/25148690

Burnham, J. F. (2006). Scopus database: A review. *Biomedical Digital Libraries*, *3*, 1. https://doi.org/10.1186/1742-5581-3-1

Canziani, B., & MacSween, S. (2021). Consumer acceptance of voice-activated smart home devices for product information seeking and online ordering. *Computers in Human Behavior*, *119*, 106714. https://doi.org/10.1016/j.chb.2021.106714

Chen, C. F., Xu, X., Adams, J., Brannon, J., Li, F., & Walzem, A. (2020). When East meets West: Understanding residents' home energy management system adoption intention and willingness to pay in Japan and the United States. *Energy Research and Social Science*, *69*, 101616. https://doi.org/10.1016/j.erss.2020.101616

Chen, C. F., Xu, X., & Arpan, L. (2017). Between the technology acceptance model and sustainable energy technology acceptance model: Investigating smart meter acceptance in the United States. *Energy Research and Social Science*, *25*, 93–104. https://doi.org/10.1016/j.erss.2016.12.011

Chen, K., & Chan, A. H. S. (2011). A review of technology acceptance by older adults. *Gerontechnology*, *10*(1), 1–12. https://doi.org/10.4017/gt.2011.10.01.006.00

Cimperman, M., Makovec Brenčič, M., & Trkman, P. (2016). Analyzing older users' home telehealth services acceptance behavior-applying an Extended UTAUT model. *International Journal of Medical Informatics*, *90*, 22–31. https://doi.org/10.1016/j.ijmedinf.2016.03.002

Clutch. (2019). *33% of people plan to invest in a smart home device in the next 3 years, demonstrating the growth of IoT in the home*. https://www.prnewswire.com/news-releases/33-of-people-plan-to-invest-in-a-smart-home-device-in-the-next-3-years-demonstrating-the-growth-of-iot-in-the-home-300858930.html

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339. https://doi.org/10.2307/249008

Dirks, K. T., & Ferrin, D. L. (2002). Trust in leadership: Meta-analytic findings and implications for research and practice. *Journal of Applied Psychology*, *87*(4), 611–628. https://doi.org/10.1037/0021-9010.87.4.611

Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of price, brand, and store information on buyers' product evaluations. *Journal of Marketing Research*, *28*(3), 307–319. https://doi.org/10.2307/3172866

Etemad-Sajadi, R., & Gomes Dos Santos, G. (2019). Senior citizens' acceptance of connected health technologies in their homes. *International Journal of Health Care Quality Assurance*, *32*(8), 1162–1174. https://doi.org/10.1108/IJHCQA-10-2018-0240

Gefen, D. (2000). The role of familiarity and trust. *Omega: The International Journal of Management Science*, *28*(6), 725–737. https://doi.org/10.1016/S0305-0483(00)00021-9

Große-Kreul, F. (2022). What will drive household adoption of smart energy? Insights from a consumer acceptance study in Germany. *Utilities Policy*, *75*. https://doi.org/10.1016/j.jup.2021.101333

Gu, W., Bao, P., Hao, W., & Kim, J. (2019). Empirical examination of intention to continue to use smart home services. *Sustainability*, *11*(19), 1–12. https://doi.org/10.3390/su11195213

Gumz, J., Fettermann, D. C., Sant'Anna, Â. M. O., & Tortorella, G. L. (2022). Social influence as a major factor in smart meters' acceptance: Findings from Brazil. *Results in Engineering, 15*. https://doi.org/10.1016/j.rineng.2022.100510

Harper, R. (2003). Inside the smart home: Ideas, possibilities and methods. In *Inside the Smart Home* (pp. 1–13). Springer. https://doi.org/10.1007/b97527

Heerink, M., Kröse, B., Evers, V., & Wielinga, B. (2010). Assessing acceptance of assistive social agent technology by older adults: The Almere model. *International Journal of Social Robotics*, *2*(4), 361–375. https://doi.org/10.1007/s12369-010-0068-5

Herrero, Á., San Martín, H., & Garcia-De los Salmones, M. (2017). Explaining the adoption of social networks sites for sharing user-generated content: A revision of the UTAUT2. *Computers in Human Behavior*, *71*, 209–217. https://doi.org/10.1016/j.chb.2017.02.007

Higgins, J. P., & Green, S. (2008). *Cochrane handbook for systematic reviews of interventions: Cochrane book series*. John Wiley and Sons. https://doi.org/10.1002/9780470712184

Juric, J., & Lindenmeier, J. (2019). An empirical analysis of consumer resistance to smart-lighting products. *Lighting Research and Technology*, *51*(4), 489–512. https://doi.org/10.1177/1477153518774080

Kelley, T. L. (1927). *Interpretation of educational measurements*. World Book Inc.

Kohnke, A., Cole, M. L., & Bush, R. (2014). Incorporating UTAUT predictors for understanding home care patients' and clinicians' acceptance of healthcare telemedicine equipment. *Journal of Technology Management and Innovation*, *9*(2), 29–41. https://doi.org/10.4067/S0718-27242014000200003

Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How habit limits the predictive power of intention: The case of information systems continuance. *MIS Quarterly: Management Information Systems*, *31*(4), 705–737. https://doi.org/10.2307/25148817

Mamonov, S., & Koufaris, M. (2020). Fulfillment of higher-order psychological needs through technology: The case of smart thermostats. *International Journal of Information Management*, *52*, 102091. https://doi.org/10.1016/j.ijinfomgt.2020.102091

Marikyan, D., Papagiannidis, S., & Alamanos, E. (2019). A systematic review of the smart home literature: A user perspective. *Technological Forecasting and Social Change*, *138*, 139–154. https://doi.org/10.1016/j.techfore.2018.08.015

Martín-Martín, A., Orduna-Malea, E., Thelwall, M., & Delgado López-Cózar, E. (2018). Google Scholar, Web of Science, and Scopus: A systematic comparison of citations in 252 subject categories. *Journal of Informetrics*, *12*(4), 1160–1177. https://doi.org/10.1016/j.joi.2018.09.002

Mashal, I., & Shuhaiber, A. (2019). What makes Jordanian residents buy smart home devices? A factorial investigation using PLS-SEM. *Kybernetes*, *48*(8), 1681–1698. https://doi.org/10.1108/K-01-2018-0008

Maswadi, K., Ghani, N. A., & Hamid, S. (2022). Factors influencing the elderly's behavioural intention to use smart home technologies in Saudi Arabia. *PLoS ONE*, *17*, 1–30. https://doi.org/10.1371/journal.pone.0272525

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, *20*(3), 709–734. https://doi.org/10.2307/258792

McCloskey, D., & Bennett, G. (2020). Examining artificial intelligence acceptance: Exploring smart speaker adoption with the unified theory of acceptance and use of technology (UTAUT2). *Pennsylvania Economic Review*, *27*(2), 44–56.

Meyer-Waarden, L., Cloarec, J., Adams, C., Aliman, D. N., & Wirth, V. (2022). Home, sweet home: How well-being shapes the adoption of artificial intelligence-powered apartments in smart cities. *Systemes d'Information et Management*, *26*(4), 55–88. https://doi.org/10.3917/sim.214.0055

Michler, O., Decker, R., & Stummer, C. (2019). To trust or not to trust smart consumer products: A literature review of trust-building factors. *Management Review Quarterly*, *70*, 391–420. https://doi.org/10.1007/s11301-019-00171-8

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., Altman, D., Antes, G., Atkins, D., Barbour, V., Barrowman, N., Berlin, J. A., Clark, J., Clarke, M., Cook, D., D'Amico, R., Deeks, J. J., Devereaux, P. J., Dickersin, K., Egger, M., Ernst, E., … Tugwell, P. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine*, *6*(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097

Moon, Y. J., & Hwang, Y. H. (2016). A study of effects of UTAUT-based factors on acceptance of smart health care services. *Lecture Notes in Electrical Engineering*, *354*, 495–501. https://doi.org/10.1007/978-3-662-47895-0

Nikou, S. (2019). Factors driving the adoption of smart home technology: An empirical assessment. *Telematics and Informatics*, *45*, 101283. https://doi.org/10.1016/j.tele.2019.101283

Oyinlola Ayodimeji, Z., Janardhanan, M., Marinelli, M., & Patel, I. (2021). Adoption of smart homes in the UK: Customers' perspective. *Lecture Notes in Mechanical Engineering*, 19–30. https://doi.org/10.1007/978-981-15-9956-9_5

Pal, D., Funilkul, S., Charoenkitkarn, N., & Kanthamanon, P. (2018). Internet-of-things and smart homes for elderly healthcare: An end user perspective. *IEEE Access*, *6*, 10483–10496. https://doi.org/10.1109/ACCESS.2018.2808472

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, *7*(3), 101–134. https://doi.org/10.1080/10864415.2003.11044275

PricewaterhouseCoopers. (2016). *Smart home technology - internet of things or indifference to things?* https://pwc.blogs.com/press_room/2016/05/smart-home-technology-internet-of-things-or-indifference-to-things-pwc-survey.html

Reinisch, C., Kofler, M. J., Iglesias, F., & Kastner, W. (2011). Thinkhome energy efficiency in future smart homes. *Eurasip Journal on Embedded Systems*, 104617. https://doi.org/10.1155/2011/104617

Shanthana Lakshmi, S., & Gupta, D. (2021). The smart set: A study on the factors that affect the adoption of smart home technology. *Machine Learning for Predictive Analysis*, 443–450.

Shuhaiber, A., & Mashal, I. (2019). Understanding users' acceptance of smart homes. *Technology in Society*, *58*, 101110. https://doi.org/10.1016/j.techsoc.2019.01.003

Sorwar, G., Aggar, C., Penman, O., Seton, C., & Ward, A. (2022). Factors that predict the acceptance and adoption of smart home technology by seniors in Australia: a structural equation model with longitudinal data. *Informatics for Health and Social Care*, 1–15. https://doi.org/10.1080/17538157.2022.2069028

Sovacool, B. K., & Furszyfer Del Rio, D. D. (2020). Smart home technologies in Europe: A critical review of concepts, benefits, risks and policies. *Renewable and Sustainable Energy Reviews*, *120*, 109663. https://doi.org/10.1016/j.rser.2019.109663

Strategy Analytics. (2019). *Consumer spending on smart home systems worldwide from 2014 to 2023 (in billion U.S. dollars)*. Statista. https://www-statista-com.ezproxy.lib.ukm.si/statistics/693303/smart-home-consumer-spending-worldwide/

Taiwo, A. A., & Downe, A. G. (2013). The theory of user acceptance and use of technology (UTAUT): A meta-analytic review of empirical findings. *Journal of Theoretical and Applied Information Technology*, *49*(1), 48–58. https://doi.org/10.12691/ajis-3-2-3

Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2019). Use of 'Habit' is not a habit in understanding individual technology adoption: A review of UTAUT2 based empirical studies. In *IFIP International Federation for Information Processing* (Vol. 533). Springer International Publishing. https://doi.org/10.1007/978-3-030-04315-5

Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2020). Consumer acceptance and use of information technology: A meta-analytic evaluation of UTAUT2. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-020-10007-6

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly: Management Information Systems, 27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Vimalkumar, M., Sharma, S. K., Singh, J. B., & Dwivedi, Y. K. (2021). 'Okay google, what about my privacy?': User's privacy perceptions and acceptance of voice based digital assistants. *Computers in Human Behavior*, *120*, 106763. https://doi.org/10.1016/j.chb.2021.106763

Wang, X., McGill, T. J., & Klobas, J. E. (2020). I want it anyway: Consumer perceptions of smart home devices. *Journal of Computer Information Systems*, *60*(5), 437–447. https://doi.org/10.1080/08874417.2018.1528486

Yang, H., Yu, J., Zo, H., & Choi, M. (2016). User acceptance of wearable devices: An extended perspective of perceived value. *Telematics and Informatics*, *33*(2), 256–269. https://doi.org/10.1016/j.tele.2015.08.007

YouGov. (2018). *In your opinion, what are the disadvantages of smart homes?* Statista. https://www-statista-com.ezproxy.lib.ukm.si/statistics/965019/opinion-on-home-automation-disadvantages-in-italy/

Zaharia, S., & Würfel, M. (2021). Voice commerce - Studying the acceptance of smart speakers. *International Conference on Human Interaction and Emerging Technologies*, 449–454.

Authors' Note

All correspondence should be addressed to
Nejc Plohl
Department of Psychology,
University of Maribor,
Koroska cesta 160, 2000 Maribor, Slovenia
Email: nejc.plohl1@um.si
Telephone: +386 2 229 3855

Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 20(1), May 2024, 114-130

UNVEILING THE NEXUS OF TECHNOLOGY ACCEPTANCE IN HEALTHCARE: EMPIRICAL EXPLORATION OF THE MULTIFACETED DRIVERS

Iga Rudawska
Institute of Economics and Finance
University of Szczecin
Poland
ORCID 0000-0002-2173-931X

Katarzyna Krot
Faculty of Engineering Management
Bialystok University of Technology
Poland
ORCID 0000-0002-7404-1724

Małgorzata Porada-Rochoń
Institute of Economics and Finance
University of Szczecin
Poland
ORCID 0000-0002-3082-5682

Abstract: *In the rapidly evolving landscape of healthcare, the integration of cutting-edge technologies has become pivotal for enhancing patient care, optimizing operational efficiency, and driving overall advancements in the field. However, the successful adoption of these technologies hinges upon the acceptance and utilization by healthcare stakeholders, particularly patients. Unraveling the complexities of technology acceptance in the healthcare domain necessitates a nuanced understanding of the underlying factors that shape individuals' attitudes and behaviors towards technology. This paper aims to provide a holistic understanding of the support factors that influence health technology acceptance. To explore these drivers (variables), 5 study hypotheses were made using the PSL-SEM model based on a developed questionnaire. The obtained results suggest that systemic support for the development of ICT in healthcare has a stronger positive impact on patients' intention to use ICT than professional support. On the other hand systemic support does not affect patients' self-efficacy unlike professional support.*

Keywords: *health sector, information technology, technology acceptance models, ICT drivers, patients' intention to use, survey, SEM*

DOI: https://doi.org/10.14254/1795-6889.2024.20-1.6

INTRODUCTION

In recent decades, the healthcare sector has witnessed an unprecedented transformation propelled by rapid advancements in Information and Communication Technology (ICT). The integration of digital technologies into healthcare practices has not only streamlined administrative processes but has also revolutionized patient care, research, and overall healthcare delivery (Nisha et al., 2015). From improving diagnostic accuracy and treatment precision to fostering proactive healthcare management and preventive strategies, ICT has become an indispensable catalyst for innovation in healthcare delivery (Yu et al., 2006; Duarthe & Pinho, 2019). The advent of electronic health records (EHRs), telemedicine, wearable devices, and data analytics has ushered in a new era, where the healthcare ecosystem is becoming increasingly interconnected and data-driven. These technological innovations have not only enhanced the accessibility and quality of healthcare services but have also presented novel challenges and ethical considerations that demand careful scrutiny (Sun & Qu, 2015).

In an era characterized by rapid technological advancements (Bilan et al., 2023; Florek & Lewicki, 2022; Remeikiene et al., 2021), the integration of innovative solutions in the healthcare sector has become pivotal for enhancing patient care, improving outcomes, and optimizing healthcare delivery systems. The emergence of health technologies, ranging from wearable devices and mobile applications to advanced medical equipment and telehealth platforms, promises to revolutionize the landscape of healthcare. However, the successful implementation of these technologies relies heavily on their acceptance by healthcare professionals, administrators and patients (Dwivedi et al., 2019; Gagnon et al., 2015; Lotfi et al., 2020). Unraveling the complexities of technology acceptance in the healthcare domain necessitates a nuanced understanding of the underlying models and the myriad factors that shape individuals' attitudes and behaviors towards technology (Mehra et al., 2020). Particularly, understanding the support factors that influence the acceptance of health technologies by patients is paramount to unlocking their full potential and ensuring widespread adoption across diverse healthcare settings.

The burgeoning field of technology acceptance models (TAMs) serves as a theoretical framework to decipher the intricate interplay between individuals and technology in the healthcare sector (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh et al., 2012). TAMs, rooted in psychological and behavioral theories, offer a structured lens through which researchers and practitioners can scrutinize the multifaceted dynamics influencing the acceptance and utilization of health technologies. The backdrop of the study lies in the imperative to bridge the gap between technological innovation and its effective implementation in healthcare settings. While the potential benefits of technologies such as electronic health records, telemedicine, wearable devices, and artificial intelligence are vast, their successful integration requires a deep understanding of the support factors that influence the acceptance or resistance to change among diverse stakeholders, particularly patients (Tam et al., 2020).

Therefore, this paper embarks on a comprehensive exploration of health technology acceptance, delving into the intricate interplay of psychological, organizational, and systemic drivers that shape individuals' willingness to embrace and effectively utilize these innovations. The significance of understanding these factors cannot be overstated, as it directly impacts the efficacy, efficiency, and ultimately the success of health technology implementations (Wu 2018). Our study adopts an interdisciplinary approach, drawing on insights from technology acceptance models, behavioral psychology, and healthcare management. By synthesizing and analyzing existing literature and performing an empirical study, we aim to unravel the key support factors that impact the technology intention to use among patients in Poland. We construct a structural framework that elucidates the interplay of various drivers influencing ICT intention to use among patients in healthcare. This paper embarks on a comprehensive exploration of these factors, shedding light on their conceptual foundations, and applicability within the healthcare context.

.

THEORETICAL APPROACHES ON TECHNOLOGY ADOPTION IN HEALTHCARE

Information and Communication Technologies (ICT) in health, often referred to as Health ICT or eHealth (electronic health), encompass a broad range of digital and analogue technologies and tools that facilitate the capturing, processing, storage, and exchange of information via electronic communication (Gagnon et al., 2009). Key components of ICT in health include: Electronic Health Records (EHRs), Telemedicine and Telehealth, Health Information Exchange (HIE), Mobile Health (mHealth), Health Information Systems (HIS), Clinical Decision Support Systems (CDSS), Health Analytics, and E-learning and Health Education (Wienstein et al., 2018; Aanestad et al., 2017). In terms of healthcare delivery and patients' relationship telemedicine and telehealth play a significant role. These technologies involve the use of electronic information and telecommunications technologies to support long-distance clinical health care, patient and professional health-related education, public health, and health administration (Richmond et al., 2017). Telemedicine can include video consultations, remote monitoring of patients, and the exchange of health information through secure communication channels (Kruse et al., 2017; Lewicki et al., 2021, Rahi et al, 2021).

From the 1960s onwards scholars have proposed many approaches to understand the attitudes, the intention to use and the behaviors towards the adoption of ICT (Lemos de Almeida et al., 2017). Exploring the influence of intentions on individual behavior has led to the development of two prominent theories: the Theory of Reasoned Action (TRA) by Fishbein and Ajzen (1975) and the Theory of Planned Behavior (TPB) by Ajzen (1985). TRA was designed to explain and predict human social behavior, especially in the context of decision-making regarding health-related behaviors, attitude change, and social influence. The central idea of TRA is that individuals are rational actors who make decisions based on a combination of their attitudes and subjective norms. Over time, Fishbein and Ajzen expanded on the TRA and developed the TPB, which includes an additional component called Perceived Behavioral Control (PBC). According to TPB, individuals are more likely to accept and use a health technology if they have a positive attitude toward it, perceive social pressure to use it, and believe they have control over its use (Ajzen, 1991).

Technology Acceptance Model (TAM) is the most popular framework, explaining the technology intention to use. It has been developed by Davis (1989) with the goal of validating measurement scales for perceived usefulness and ease of use. These constructs represent an individual's belief in a system's utility for enhancing work performance and the perceived effort required to use the system, respectively. Davis focused on user acceptance, linking perceived usefulness and ease of use to usage intention and behavior. Furthermore, Davis, Bagozzi, and Warshaw (1989) emphasized the need for a foundation to assess the impact of external drivers on beliefs, attitudes, and internal intentions in technology acceptance. They measured intentions in terms of attitudes, subjective norms, perceived usefulness, perceived ease of use, and related variables. In turn Venkatesh and Davis (2000) introduced TAM2 – an extension of the original model to account for additional factors and contextual considerations in understanding technology adoption. Their modification includes new constructs such as social influence, cognitive instrumental processes, subjective norms, voluntariness, image, job relevance perception, output quality, and demonstrability of results.

Next, Venkatesh et al. (2003) and Venkatesh, Thong, and Xu (2012) developed a unified model (Unified Theory of Acceptance and Use of Technology - UTAUT), based on TAM, incorporating four key predictors of technology acceptance: performance expectancy, effort expectancy, social influence, and facilitating conditions. It also considers moderating factors such as gender, age, and experience. In the realm of e-health, researchers such as Hoque and Sorwar. (2017), Kaium et al. (2020), and Seethamraju, Diatha, and Garg (2018) have applied this theory to investigate user behavior regarding the adoption of e-health services. Inhibiting and facilitating drivers have been also considered by Ratchford and Barnhart (2012), who addressed the propensity of use, evaluating the attitudes and beliefs of potential technology users and non-users.

Social influence is a key component of UTAUT, being understood as "the degree to which a patient believes in the recommendations of significant others regarding the adoption of telemedicine health services" (Cho 2016; Venkatesh, Thong, and Xu 2012). According to previous studies social influence has demonstrated a positive influence on patient behavior in embracing telemedicine (Cho 2016; Kaium et al. 2020; Zhou & Li 2014). Researchers such as Kaium et al. (2020), Ahmad and Khalid (2017) and Sun et al. (2012) have proved the significant effect of social influence on user behavior in sustaining the use of m-health services. It is important to stress that Ward et al. (2017) found that healthcare practitioners play an important role in stimulating the acceptance and use of technologies. This subject had gained little exploration so far, although the impact of healthcare professionals on the acceptance of health information technology have been incorporated into another model called Health Information Technology Acceptance Model – HITAM (Aggelidis &Chatzoglou, 2009; Rashid et al., 2018).

On the other hand, facilitating condition is acknowledged as "the extent to which a patient believes that organizational infrastructure enables him/her to use telemedicine health services" (Venkatesh et al., 2012). Scholars like (Deng 2013), Aggelidis and Chatzoglou (2009) and Nysveen and Pedersen (2016) have confirmed that the presence of infrastructure encourage patients and enhances their proficiency in utilizing telehealth and telemedicine. Further, various other researchers have revealed that facilitating conditions exert a significant impact on the intention and/or actual usage of technology (Mun et al. 2006; Aggelidis & Chatzoglou, 2009; Deng 2013, Alam et al., 2020).

THE MEDIATING ROLE OF SELF-EFFICACY

Investigations into the acceptance of consumer health technology have predominantly employed the TAM or its updated iterations (UTAUT) as a foundational theoretical framework (Tao et al., 2018; Tao et al., 2016). Despite their broad applicability, there exists a necessity for its modification through the incorporation of contextual and theoretically justified factors. Such factors aim to enhance the model's predictive efficacy within specific contexts (Priyansyah et al., 2023).

In the specific domain of ICT in healthcare the challenge of non-acceptance appears to be intricately linked to patients' initial interaction experiences with the applications (Tao et al., 2020). These experiences are predominantly shaped by self-efficacy. It refers to users' self-perceptions regarding their capability to effectively utilize the applications (Douneva et al., 2016). Therefore, a comprehensive understanding of acceptance issues in the context of healthcare settings necessitates the integration of the self-efficacy into the research framework.

The meaningful exploration for self-efficacy is delivered by Social Cognitive Theory - SCT (Maddux, 1993; Badura, 2004). SCT posits that self-efficacy assumes a preponderant function in directing individual conduct within the domain of technological utilization (Vancouver & Purl, 2017). If patients perceive themselves as incapable of executing prescribed tasks using a particular eHealth application, their persistence in its utilization may falter. Consequently, self-efficacy, particularly in relation healthcare settings, seems to be instrumental in fostering intention to use and delineating patient approval (Ma & Liu, 2005).

Earlier investigations have demonstrated the influence of self-efficacy particularly on the perceived utility and perceived ease of use of technology in a broad sense (Kulviwat et al., 2014), including applications in health informatics (Tsai, 2014). Moreover, it has been proposed by Compeau and Higgins (1995) that the predictive efficacy of the self-efficacy construct can be enhanced by contextualizing it through a domain-specific measure, as opposed to its generic manifestation. A substantial number of previous studies (Bilgrami et al., 2020; Tang et al., 2019; Deng & Liu, 2017) have proved that individuals possessing elevated levels of self-efficacy exhibit affirmative intentions to adopt telemedicine applications, thereby facilitating effective disease management. Kohnke et al. (2014) also prove that he cognitive constructs of self-efficacy beliefs exert a decisive influence on cognitive processes, emotional states, motivational propensities, and behavioral manifestations in individuals. This influential role extends to their proclivity to engage with information technology, thereby significantly impacting both the intention to employ such technology and the subsequent actual utilization behaviors.

RESEARCH METHODOLOGY

Research Model

In the study, modern technologies in healthcare were defined as any health solution that is new to the patient and based on information, ICT and communication technologies, e.g.: televisions, conversations with virtual consultants, modern medical devices used remotely in diagnosis, therapy and rehabilitation. The term new technologies also includes online patient-doctor communication platforms and applications for patient care management and patient self-care.

Moreover, we perceive social influence in terms of professional support (PS), provided by physicians to patients in healthcare settings. We define PS as the degree to which doctors, clinicians and caregivers support patients' use of ICT. On the other hand, facilitating condition is perceived as systemic support (SS), performed by government a various levels, enabling patients access to infrastructure and information about ICT solutions when needed. A substantial number of studies has confirmed that both social influence and facilitating conditions positively effect on patient intention to adapt telemedicine and telecare. Thus back up by earlier studies following hypotheses are proposed:

H1: Systemic support has positive influence on patient's intention to use modern technologies in healthcare

H2: Professional support has positive influence on patient's intention to use modern technologies in healthcare

As highlighted in the previous section, self-efficacy may significantly impact the behavior intention of the individuals in accepting technologies in healthcare settings. Consequently, this study delves into the assessment of patients' self-efficacy (SE). This construct is defined as an individual's evaluative judgment regarding their own proficiency in utilizing new technologies for the acquisition of health-related information and services. The present study contributes to the existing body of knowledge and elucidates computer self-efficacy's role as a mediating variable in the relationship among both systemic support and professional support and the intention of patients to adopt new technologies in health services. Thus, these relationships are hypothesized as:

H3: The systemic support has positive influence on patient's self-efficacy

H3a: The relationship between systemic support and intention to use modern technologies is positively mediated by patient's self-efficacy

H4: The professional support has positive influence on patient's self-efficacy

H4a: The relationship between professional support and intention to use modern technologies is positively mediated by patient's self-efficacy

H5: Patient's self-efficacy has positive influence on patient's intention to use modern technologies in healthcare

The proposed research model as depicted in Figure 1 presents all hypothesized relations among identified constructs. He current study advances the body of knowledge by examining the mediating impact of patient's self-efficacy between systemic and professional support and intention to use new technologies by patients in Poland. The model is based on the unified theory of acceptance, referring to the fundamental role of facilitating drivers (here: support by regulatory bodies) and social influence (here: organizational and professional support). The current study develops an integrated research model to examine patients' intention towards the adoption of new technologies in healthcare settings in Poland.

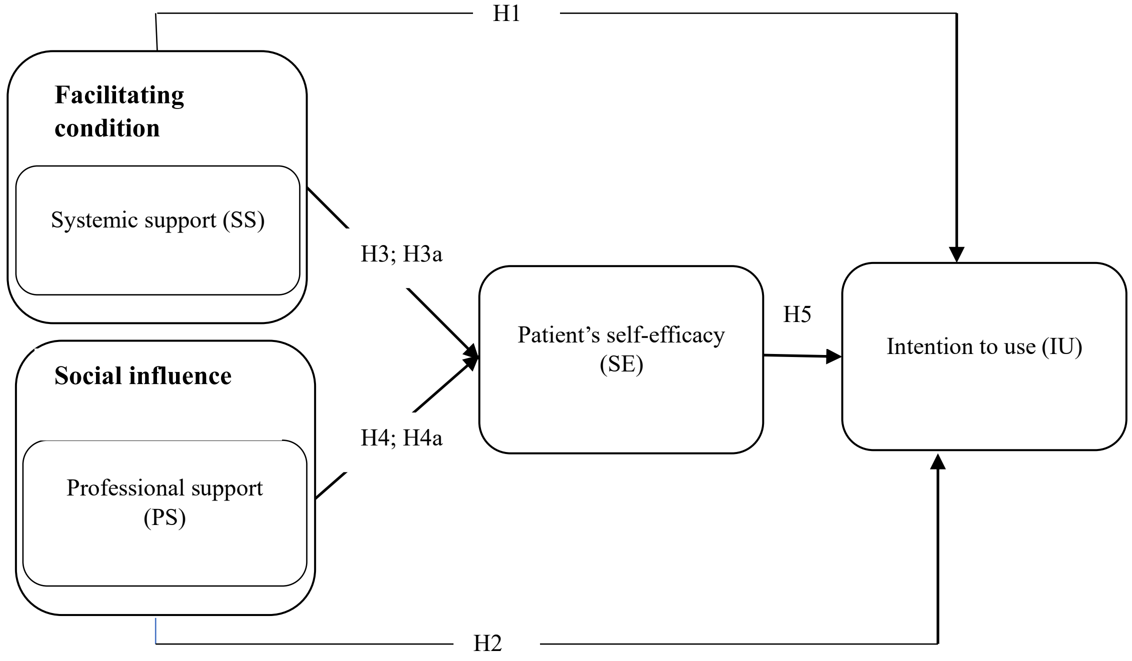

Figure 1. The proposed research model
[Source: own work]

Table 1. Scale characteristics [Source: own work]

Variable	Source	Cronbach Alpha
Systemic support (7 items)	Li & Atuahene-Gima (2001); Shu et al. (2019); Lean et al. (2009);	0,91
Professional support (10 items)	Wu (2018); Ward et al. (2007);	0,96
Intention to use (4 items)	Priyansyah et al. (2023); Shareef et al. (2014); Ahmed et al. (2023);	0,91
Self-efficacy (4 items)	Sun et al. (2013); Gao et al. (2015), Tao et al. (2020);	0,92

The study assumed that a patient who is convinced of new technologies will declare his intention to use these technologies if the need arises. This variable was measured by 4 statements depicting the willingness to use new technologies in the health area more and more in the future. The Alpha Cronbach index for this scale assumed a value of 0.91.

The construct of *systemic support* (government institutional support), on the other hand, was measured by 7 statements, which indicated that health system institutions provide patients with the information necessary to learn about new technologies, provide access to infrastructure to ensure the use of new technologies, encourage patients to use modern technologies, and are aware of the benefits that can be achieved through the use of new technologies. The Alpha Cronbach index for this scale assumed a value of 0.91.

The variable *professional support* for the development of new technologies" is a construct consisting of 10 statements, among others, emphasizing doctors' concern for the safety, convenience and comfort of patients when using new technologies and proper communication in the doctor-patient relationship regarding new technologies. The Alpha Cronbach index for this scale assumed a value of 0.96.

In addition, the *intention to use* new technologies in medicine was considered to be determined by the perception of *self-efficacy* in this regard. Therefore, this variable was entered into the model as a mediating variable, consisting of 4 assertions. These statements related to the ease of using modern technologies in daily life, even without the help of third parties. The Alpha Cronbach index for this scale assumed a value of 0.92.

DATA COLLECTION

For data collection, an online survey was carried out. The survey was conducted in January-February 2022 using the CAWI technique on a representative sample of 1,074 adult residents of Poland. Those invited to participate in the survey were those who had used medical care in the last six months before the survey. Information on the socio-demographic structure of the survey sample can be found in the Table 2.

Table 2. Research sample structure (N=1074) [Source: own work]

	Number	%		Number	%
Sex			**Place of residence**		
Female	584	54,4	Countryside	354	32,9
Male	490	45,6	Small town (up to 20 000 residents)	123	11,5
Education			Middle-size town (20 000- 99 000 residents)	233	21,7
Primary	27	2,5	Big town (100 000-500 000 residents)	222	20,7
Vocational	105	9,8	City (over 500 000 residents)	142	13,2
Secondary	433	40,3	**Net income per capita**		
Bachelor	114	10,6	Up to 1500 PLN	198	18,4
Master	395	36,8	1501-2000 PLN	200	18,6
Age			2001-2500 PLN	176	16,4
18-24	124	11,5	2501-3000 PLN	174	16,2
25-34	264	24,6	3001-3500 PLN	121	11,3
35-44	252	23,5	Over 3500 PLN	205	19,1
45-54	202	18,8			
55 and over	232	21,6			

The demographic profile of the respondents indicate that among 1074 individuals 584 were female and 490 respondents were male. Concerning with respondents age there were 11,5% less than 25 years old, 24,6% were having age 25 to 34 and 23,5% had an age range 35-44. Similarly, 18,8% of respondents were having age 45-54 and 21,6% were older than 54. As much as 40% of respondents had secondary education, while 10,6% had bachelor degree and 24,6% held master degree. Respondents with primary education were found at the lowest level only 2,5%, and those with vocational education: 9,8%. The distribution of net income per capita was quite balanced across the sample. Almost on third of the respondents live in the countryside, while 11,5% in a small town, 21,7% in a middle-size town and 20,7% in a big town. Only 13,7% of the respondents live in a city.

RESEARCH RESULTS

To verify the theoretical model, structural equation modelling (SEM) was used, which is a linear cross-sectional statistical modelling technique including path analysis and regression analysis. The SEM is used to explain the pattern of a series of interrelated dependence relationships simultaneously between a set of latent constructs. In addition, SEM is also used to estimate variance and covariance, test hypotheses, conventional linear regression, and factor analysis (Jöreskog & Sörbom, 1996). However, an SEM-tested model must be based on theoretical assumptions and it is the only theory that can stimulate and trigger the development or modification of the model. Because SEM is mostly used to determine whether a certain model is valid rather than to "find" a suitable model, it is the most applicable statistical method to validate the proposed model (Figure 1). This is where the theory plays an important role in justifying the model.

To verify the theoretical model, the maximum likelihood (ML) estimation method was applied. The ML function is a structured means model reflecting how closely the sample mean vector is reproduced by the estimated model mean vector. It is also indicated how closely the sample covariance matrix is reproduced by the estimated model covariance matrix (Bentler, 1995). Moreover, to assess the quality/fit of the model, the following indexes were used: GFI (goodness fit index), CFI (comparative fit index) and RMSEA (root mean square error of approximation).

The descriptive statistics of the variables are presented in Table 3. It is worth noting that some of the dependencies are negative.

Table 3. Descriptive statistics [Source: own work]

	Mean	SD	Systemic support	Professional support	Intention to use
Systemic support	3,10	5,82	1,00		
Professional support	3,00	9,46	0,71		
Intention to use	3,78	3,10	0,30	0,31	
Self-efficacy	3,80	3,20	0,18	0,20	0,67

The results revealed a $\chi 2$ of 1009.4 based on 270 degrees of freedom with a probability level of 0.00. As the indicators show, the goodness-of-fit measures of the model are satisfactory (Table 4).

Table 4. The goodness of fit indexes [Source: own work]

Index	Score
CMIN/DF	3,73
GFI	0.92
CFI	0.97
RMSA	0.05
Holter	348

All model paths, except one, are statistically important. Thus four out of five hypotheses have been confirmed (Table 5).

Table 5. Standardized Regression Weights [Source: own work]

					Estimate	Status of hypothesis
H1		Intention to use	<---	Systemic support	0,14	support
H2		Intention to use	<---	Professional support	0,07	support
H3		Self-efficacy	<---	Systemic support	-	rejected
H3a	Intention to use <---	Self-efficacy	<---	Systemic support	-	rejected
H4		Self-efficacy	<---	Professional support	0,21	support
H4a	Intention to use <---	Self-efficacy	<---	Professional support	0,15	support
H5		Intention to use	<---	Self-efficacy	0,70	support

Seven hypotheses have been proposed in the model based on the previous findings. Five of them (H1, H2, H4, H4a and H5) have been statistically confirmed. In turn, there are two hypotheses (H3 and H3a) that have not been confirmed. It turned out that systemic support for the development of ICT in healthcare does not increase patients' self-efficacy in the use of these technologies. Instead, this feeling is quite significantly perpetuated by the professional support of physicians (H4). Thus, it appears that physicians, as part of their direct contact with patients and their attitudes toward technology, can shape patients' beliefs about their ability to use modern technologies. Systemic support for the development of ICT in healthcare definitely has a stronger positive impact on patients' intention to use these technologies than professional/ organizational support (H1 and H2). However, according to respondents, patients' intention to use modern technologies is definitely impacted by their self-efficacy in this regard (H5).

Thus, considering the two types of drivers to use ICT in healthcare, i.e., systemic and professional / organizational support, the former more strongly influences patients' intention to use technology, but on the other hand does not affect patients' self-efficacy in this regard. Professional support, on the other hand, impacts less the intention to use, but influences patients' self-efficacy, which in turn strongly determines their intention to use technology. Therefore, it would be interesting to see what the total impact of the different types of support is on the patients' intention to use technology in healthcare settings. For this purpose, the direct and indirect influences on intention to use were examined.

Considering the two types of analyzed support (systemic versus organizational), it turned out that the support of physicians more strongly determines intention to use than systemic support (Table 6). The analysis showed that in the case of systemic support, patients' self-efficacy is not a mediating factor, i.e. it does not mediate in encouraging patients to use modern technology (H3a). A completely different situation applies to professional support. In this case, the direct effect on intention to use is small, but the introduction of the self-efficacy variable increased the strength of the effect (H4a). This means that familiarizing patients with modern technology by doctors improves their self-efficacy, which in turn significantly increases patients' willingness to use them when necessary.

Table 6. Standardised total, indirect and direct effects [Source: own work]

	Systemic support	Professional support	Self-efficacy
Standardized Total Effects			
Self-efficacy	0,00	0,21	
Intention to use	0,14	0,22	0,7
Standardized Direct Effects			
Self-efficacy	0,00	0,21	-
Intention to use	0,14	0,07	0,7
Standardized Indirect Effects			
Self-efficacy	0,00	0,00	
Intention to use	0,00	0,15	

DISCUSSION

Several researchers (Ward et al., 2007; Shareef et al., 2014; Wu, 2018; Priyansyah et al., 2023, Ahmed et al., 2023) have attempted to conceptualize and restructure the technology acceptance in healthcare. Although consumers of medical services are the most important link in the service delivery chain, their intention to use ICT and subsequently their adoption behavior has not been explored in the Polish healthcare settings comprehensively so far. Therefore, the present study sought to evaluate and theorize the adoption behavior of general consumers who engage in the health system as patients. The authors accomplished the research objective by developing a conceptual model highlighting the driving forces in adopting modern technologies in healthcare.

Our findings are in addition to the concept of UTAUT (Tao et al., 2018; Tao et al., 2016) and are justified in the perspective of e-health organizational and technological nature based on the concept of TRA (Fishbein & Ajzen, 1975) and TPB (Ajzen, 1985). The results of our study strengthen the premise that e-health adoption behavior is a final outcome shaped not only by patients' beliefs in technology but also by social and institutional beliefs (Shareef et al., 2014). Therefore, our findings are in line with the research results obtained by Zhou & Li (2014), Cho (2016), Ahmad and Khalid (2017) and Kaium et al. (2020). All these studies explored and empirically confirmed the significant effect of social influence on user behavior in sustaining the use of m-health services. Moreover, our findings are in line with those obtained by Ward et al. (2017), who found that medical doctors play a crucial role in reinforcing the acceptance and usage of ICT by patients.

Moreover, our research confirmed that institutional, systemic support is a significant driver, stimulating the intention to use of modern technologies in healthcare setting, although it does not impact the patient's self-efficacy. This result supported by some studies exploring facilitating conditions for M-health (Mun et al. 2006; Aggelidis & Chatzoglou, 2009) and some other studies discussing external, governmental issues impacting the intention to use modern technology in healthcare (Deng 2013, Alam et al., 2020). Therefore, under the institutional context of e-health, the patients' perception of reliability of the overall system contributes significantly to their adoption behavior. The similar conclusions have been drawn by Li & Atuahene-Gima (2001), Lean et al. (2009) and Shu et al. (2019).

Finally, with our study we confirmed the important role of patients' self-efficacy in shaping the intention to use of ICT in health system, although according to our research it is not stimulating by institutional support. Our empirical investigation strengthens the premise done other researchers (Deng & Liu, 2017; Tang et al., 2019; Bilgrami et al., 2020) that patients demonstrating higher levels of self-efficacy show affirmative intentions to adopt ICT in the service delivery process. Moreover, it turned out that self-efficacy strengthens doctors' actions aimed at encouraging patients to use modern technology (becoming an important mediating variable, Ma & Liu, 2005; Tao et al., 2020). However, a similar effect could not be observed in the case of systemic support.

CONCLUSIONS

Our research has been designed on a conceptual model exploring the crucial drivers stimulating adoption of modern technologies in health system. We explored two types of drivers: systemic and professional support. The findings contribute to the overall understanding of the factors underling he patients' intention to adopt and finally to use ICT in healthcare settings. The value of the study is based on the discovery of the impact of the both systemic / institutional and professional / organizational factors on patients' self-efficacy and finally their adoption of e-health.

However, although with our research we contribute significantly to the scare literature in the field of ICT adoption by end-users (patients), the study has some limitations. Frist of all our study examined only two types of drivers enhancing usage of ICT in healthcare. It would be interesting to incorporate psychological factors into the research model in the subsequent studies. Another limitation of the study is the region. Since the study was conducted in Poland whose health sector can be classified as low technology saturated, its results cannot be generalized for developed countries. Therefore, it would be recommended to replicate the research process in both types of countries in order to identify a difference in perception of drivers in ICT adoption.

Finally, it is true to state that adoption of ICT in healthcare is a complex issue. The advent of health technologies has ushered in transformative potential, promising improved patient outcomes, enhanced communication between healthcare providers and patients, and increased operational efficiency within healthcare systems. Yet, despite these promises, the widespread acceptance of health technologies remains a complex challenge. Recognizing the diverse range of factors that shape user perceptions and behaviors towards health technologies is crucial for developing strategies that promote their seamless integration into healthcare ecosystems.

IMPLICATIONS FOR THEORY, APPLICATION, AND POLICY

With this paper we provided a nuanced understanding of the systemic, organizational and psychological factors that underpin the intention to use of health technologies. Moreover, it bridges gaps in existing literature by considering the unique challenges and opportunities within the healthcare context that impact the adoption of these technologies. Such insights are of key importance for informing policy decisions, guiding the design of user-friendly technologies, and promoting effective strategies for implementing and integrating health technologies into routine healthcare practices. As we stand at the crossroads of technological innovation and healthcare delivery, this examination serves as a timely and essential contribution to the ongoing discourse surrounding the future of health technology acceptance.

REFERENCES

Aanestad, M., M. Grisot, O. Hanseth, and P. Vassilakopoulou (2017). *Information Infrastructures for eHealth*," *Information Infrastructures within European Health Care*, M. Aanestad, M. Grisot, O. Hanseth, and P. Vassilakopoulou (eds.), Information Infrastructures within European Health Care. Health Informatics, Springer International Publishing, Cham (pp. 11-23)

Aggelidis, V. P., P. D. Chatzoglou. (2009). Using a modified technology acceptance model in hospitals *International journal of medical informatics* 78 (2), 115–126. doi:10.1016/j.ijmedinf.2008.06.006.

Ahmad, S. Z., Khalid K.. (2017). The adoption of M-government services from the user's perspectives: Empirical evidence from the United Arab Emirates. *International journal of information management 37* (5), 367–379. doi:10.1016/j.ijinfomgt.2017.03.008

Ahmed, S., Alqasmi, I., Ashrafi, D. M., Choudhury, M. M., Rahman, M. K., & Mohiuddin, M. (2023). Determining the intention to use app-based medicine service in an emerging economy. *International Journal of Healthcare Management*, 1–15. https://doi.org/10.1080/20479700.2023.2198186

Ajzen, I. (1985) *From Intentions to Actions: A Theory of Planned Behavior. In: Action Control: From Cognition to Behavior.* J. Kuhl and J. Beckmann (Eds.). Springer Verlag, New York, (pp. 11-39)

Ajzen, I. (1991) *The Theory of Planned Behavior*. Organizational Behavior and Human Decision Processes, n. 50, (pp. 179-211)

Alam, M.Z., Alam, M.M., Uddin, M.A., Mohd Noor, N.A. (2020). Do mobile health (mHealth) services ensure the quality of health life? An integrated approach from a developing country context. *Journal of Marketing Communications*, 28, 152 – 182.

Almeida, J. P. L. de, Farias, J. S., & Carvalho, H. S. (2017). Drivers of the Technology Adoption In Healthcare. *Brazilian Business Review*, *14*(3), 336–351. https://doi.org/10.15728/bbr.2017.14.3.5

Bandura, A. (2004). Health Promotion by Social Cognitive Means. *Health Education & Behavior*, 31, 143 – 164. https://doi.org/10.1177/1090198104263660.

Bentler, P. (1995). *EQS Structural Equations Program Manual*. Encino, CA: Multivariate Software.

Bilan, Y., Oliinyk, O., Mishchuk, H., & Skare, M. (2023). Impact of information and communications technology on the development and use of knowledge. *Technological Forecasting and Social Change, 191*, 122519. DOI: 10.1016/j.techfore.2023.122519

Bilgrami, Z., A. Abutaleb, K. Chudy-Onwugaje, P. Langenberg, M. Regueiro, D. A. Schwartz, ..S. M. Quezada. (2020). Effect of TELEmedicine for Inflammatory Bowel Disease on Patient Activation and Self-efficacy. *Digestive Diseases and Sciences* 65 (1), 96–103.

Compeau, D.R., & Higgins, C.A. (1995). Computer Self-Efficacy: Development of a Measure and Initial Test. MIS Q., 19, 189-211.

Cho, J. (2016). The Impact of Post-adoption Beliefs on the Continued Use of Health Apps. *International Journal of Medical Informatics* 87, 75–83.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* 13 (3), 319–340. doi:10.2307/249008.

Davis, F. D.; Bagozzi, R.P.; Warshaw, P.R. (1989) User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*,35(8), 982-1002.

Deng, Z. (2013). Understanding public users' adoption of mobile health service. *International Journal of Mobile Communications 11* (4), 351–373. doi:10.1504/IJMC.2013.055748.

Deng, Z., S. Liu. (2017). Understanding Consumer Health Information-seeking Behavior from the Perspective of the Risk Perception Attitude Framework and Social Support in Mobile Social Media Websites. *International Journal of Medical Informatics* 105, 98–109

Douneva M, Jaron R and Thielsch MT (2016). Effects of different website designs on first impressions,

aesthetic judgements and memory performance after short presentation. *Interact Comput,* 28, 552–567.

Dwivedi, Y. K., N. P. Rana, A. Jeyaraj, M. Clement, and M. D. Williams. (2019). Re-examining the unified

theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers 21* (3), 719–734. doi:10.1007/s10796-017-9774-y

Duarte, P., & Pinho, J. C. (2019). A mixed methods UTAUT2-based approach to assess mobile health adoption. *Journal of business research 102*, 140–150. doi:10.1016/j.jbusres.2019.05.022.

Fishbein, M.; Ajzen, I. (1975) Belief, attitude, intention and behavior: An introduction to theory and research. Addison-Wesley, Reading, MA

Florek, M., & Lewicki, M. (2022). Destinations, virtual reality and COVID-19. How isolation has shaped the behaviours and attitudes towards VR. *Economics and Sociology, 15*(1), 205-221. doi:10.14254/2071-789X.2022/15-1/13

Gagnon, M., Légaré, F., Labrecque, M., Frémont, P., Pluye, P., Gagnon, J., Car, J., Pagliari, C., Desmartis, M., Turcot, L., & Gravel, K. (2009). Interventions for promoting information and communication technologies adoption in healthcare professionals. *The Cochrane database of systematic reviews*, 1, CD006093. https://doi.org/10.1002/14651858.CD006093.pub2.

Gagnon, M.-P., D. Simonyan, E. K. Ghandour, G. Godin, M. Labrecque, M. Ouimet, and M. Rousseau. (2016). Factors influencing electronic health record adoption by physicians: A multilevel analysis. *International journal of information management 36* (3), 258–270. doi:10.1016/j.ijinfomgt.2015.12.002.

Gao, Y., Li, H., & Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. *Ind. Manag. Data Syst*., 115, 1704-1723

Hoque, R., and G. Sorwar. (2017). Understanding Factors Influencing the Adoption of mHealth by the Elderly: An Extension of the UTAUT Model. *International Journal of Medical Informatics* 101, 75–84.

Jöreskog, K.G. and Sörbom, D. (1996). *LISREL 8: User's Reference Guide*. Lincolnwood. Scientific Software International, Inc.

Kaium, M. A., Y. Bao, M. Z. Alam, and M. R. Hoque.(2020). Understanding continuance usage intention of mHealth in a developing country. *International Journal of Pharmaceutical and Healthcare Marketing* 14 (2), 251–272. doi:10.1108/IJPHM-06-2019-0041.

Kohnke, A., Cole, M. L., & Bush, R. G. (2014). Incorporating UTAUT Predictors for Understanding Home Care Patients' and Clinician's Acceptance of Healthcare Telemedicine Equipment. *Journal of Technology Management & Innovation*, *9*(2), 29–41. https://doi.org/10.4067/S0718-27242014000200003

Kruse, C., Krowski, N., Rodriguez, B., Tran, L., Vela, J., Brooks, M. (2017). Telehealth and patient satisfaction: a systematic review and narrative analysis. *BMJ Open*, 7. https://doi.org/10.1136/bmjopen-2017-016242.

Kulviwat, S., Bruner, G.C., & Neelankavil, J.P. (2014). Self-efficacy as an antecedent of cognition and affect in technology acceptance. *Journal of Consumer Marketing*, 31, 190-199.

Lean, O. K., S. Zailani, T. Ramayah, and Y. Fernando. (2009) Factors influencing intention to use e-government services among citizens in Malaysia.. *International journal of information management 29* (6), 458–475. doi:10.1016/j.ijinfomgt.2009.03.012.

Lewicki, A., Pancerz, K., & Puzio, L. (2021). The temporal inference with the use of ant-based clustering algorithm and flow graphs in the problem of prognosing complications of medical surgical procedures. *Human Technology*, *17*(3), 213–234. https://doi.org/10.14254/1795-6889.2021.17-3.3

Li, H., Atuahene-Gima, K. (2001). Product Innovation Strategy and the Performance of New Technology Ventures in China. *Academy of Management Journal*, 44, 1123-1134.

Lotfi, F., K. Fatehi, and N. Badie. (2020) An Analysis of Key Factors to Mobile Health Adoption using Fuzzy AHP.*I.J. Information Technology and Computer Science 2*, 1–17.

Lewicki, A., Pancerz, K., & Puzio, L. (2021). The temporal inference with the use of ant-based clustering algorithm and flow graphs in the problem of prognosing complications of medical surgical procedures. *Human Technology*, *17*(3), 213–234. https://doi.org/10.14254/1795-6889.2021.17-3.3

Li, H., & Atuahene-Gima, K. (2001). Product Innovation Strategy and the Performance of New Technology Ventures in China. *Academy of Management Journal*, 44, 1123-1134.

Lotfi, F., K. Fatehi, and N. Badie. (2020). An Analysis of Key Factors to Mobile Health Adoption using Fuzzy AHP. *I.J. Information Technology and Computer Science 2*, 1–17.

Ma, Q., L. Liu, (2005) The Role of Internet Self-Efficacy in the Acceptance of Web-Based Electronic Medical Records, *Journal of Organizational and End User Computing*, 17(1), 38-57.

Maddux, J. (1993). Social cognitive models of health and exercise behavior: An introduction and review of conceptual issues. *Journal of Applied Sport Psychology*, 5, 116-140. https://doi.org/10.1080/10413209308411310

Mehra, A., J. Paul, and R. P. S. Kaurav. (2020). Determinants of mobile apps adoption among young adults: theoretical extension and analysis. *Journal of Marketing Communications,* 1–29. doi:10.1080/13527266.2020.1725780.

Nisha, N., M. Iqbal, A. Rifat, and S. Idrish. (2015). Mobile health services: A new paradigm for health care systems. *International Journal of Asian Business and Information Management (IJABIM) 6* (1), 1–17. doi:10.4018/IJABIM.2015010101

Nysveen, H., and P. E. Pedersen. (2016). Consumer Adoption of RFID-enabled Services. Applying an Extended UTAUT Model. *Information Systems Frontiers* 18 (2), 293–314.

Priyansyah, R. N., Fuady, I., & Pratamawaty, B. B. (2023). Factors influencing acceptance of Indonesian contact tracing APP: Development of the technology acceptance model. *Human Technology*, *19*(2), (pp.262-282).

Rahi, S., Khan M.M. & Alghizzawi M. (2021) Factors influencing the adoption of telemedicine health services during COVID-19 pandemic crisis: an integrative research model, *Enterprise Information Systems*, 15(6), 769-793, DOI: 10.1080/17517575.2020.1850872

Ratchford, M.; Barnhart, M. (2012) Development and validation of the technology adoption propensity (TAP) index. *Journal of Business Research*, 65(8), 1209-1215

Remeikiene, R., Gaspareniene L., Fedajev, A., & Vebraite, V. (2021). The role of ICT development in boosting economic growth in transition economies. *Journal of International Studies*, *14*(4), 9-22. doi:10.14254/2071-8330.2022/14-4/1

Rashid, A., Abdulaziz, S., Yasin, N. (2018). Technology Acceptance Models to Improve Adoption of Health Information Systems. 1, (pp.17-29). https://doi.org/10.32441/JASET.V1I1.66

Richmond, T., Peterson, C., Cason, J., Billings, M., Terrell, E., Lee, A., Towey, M., Parmanto, B., Saptono, A., Cohn, E., & Brennan, D. (2017). American Telemedicine Association's Principles for Delivering Telerehabilitation Services. *International Journal of Telerehabilitation*, 9, 63–68. https://doi.org/10.5195/ijt.2017.6232

Shareef, M.A., Kumar, V., & Kumar, U. (2014). Predicting mobile health adoption behaviour: A demand side perspective. *Journal of Customer Behaviour*, 13, 187-205.

Shu, C., Clercq, D.D., Zhou, Y., & Liu, C. (2019). Government institutional support, entrepreneurial orientation, strategic renewal, and firm performance in transitional China. *International Journal of Entrepreneurial Behavior & Research*, 25(3), 433-456

Seethamraju, R., K. S. Diatha, S. Garg. (2018). Intention to Use a Mobile-based Information Technology Solution for Tuberculosis Treatment Monitoring–applying a UTAUT Model. *Information Systems Frontiers* 20 (1), 163–181.

Sun, Y., N. Wang, X. Guo, and Z. Peng. (2013). Understanding the acceptance of mobile health services: a comparison and integration of alternative models. *Journal of Electronic Commerce Research 14* (2), 183–200

Sun, J., & Qu Z, (2015). Understanding Health Information Technology Adoption: A Synthesis of Literature from an Activity Perspective, *Information Systems Frontiers*, 17(5), 1177-1190.

Tam, C., D. Santos, and T. Oliveira. (2020). Exploring the influential factors of continuance intention to use mobile Apps: Extending the expectation confirmation model. *Information Systems Frontiers 22* (1), 243–257. doi:10.1007/s10796-018-9864-5.

Tang, V., K. L. Choy, G. T. Ho, H. Y. Lam, and Y. P. Tsang. (2019). An IoMT-based Geriatric Care Management System for Achieving Smart Health in Nursing Homes. *Industrial Management & Data Systems* 119 (8), 1819–1840

Tao, D., Shao, F., Liu, S., Wang, T., & Qu, X. (2016). Predicting Factors of Consumer Acceptance of Health Information Technologies. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 60, 598 – 602.

Tao, D., Yuan, J., Shao, F., Li, D., Zhou, Q., & Qu, X. (2018). Factors Affecting Consumer Acceptance of an Online Health Information Portal Among Young Internet Users. CIN: *Computers, Informatics, Nursing*, 36, 530–539.

Tao D, Shao F, Wang H, Yan M, Qu X. (2020). Integrating usability and social cognitive theories with the technology acceptance model to understand young users' acceptance of a health information portal. *Health Informatics Journal*. 26(2), 1347-1362. doi:10.1177/1460458219879337

Tsai C. H. (2014). Integrating social capital theory, social cognitive theory, and the technology acceptance model to explore a behavioral model of telehealth systems. *International journal of environmental research and public health*, *11*(5), 4905–4925. https://doi.org/10.3390/ijerph110504905

Weinstein, R., Krupinski, E., & Doarn, C. (2018). Clinical Examination Component of Telemedicine, Telehealth, mHealth, and Connected Health Medical Practices. *The Medical clinics of North America*, 102 (3), 533-544. https://doi.org/10.1016/j.mcna.2018.01.002.

Wu, I.-L., Li, J.-Y., & Fu, C.-Y. (2011). The adoption of mobile healthcare by hospital's professionals: An integrative perspective. *Decision Support Systems, 51*(3), 587-596. doi: 10.1016/j.dss.2011.03.003.

Wu, B. (2018) Patient continued use of online health care communities: Web mining of patient-doctor communication. *Journal of medical Internet research 20* (4), e126. doi:10.2196/jmir.9127.

Vancouver, J., & Purl, J. (2017). A Computational Model of Self-Efficacy's Various Effects on Performance: Moving the Debate Forward. *Journal of Applied Psychology*, 102, 599–616. https://doi.org/10.1037/apl0000177.

Venkatesh, V., M. G. Morris, G. B. Davis, and F. D. Davis. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly* 27, 425–478. doi:10.2307/30036540.

Venkatesh, V., J. Y. Thong, and X. Xu. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly 36* (1), 157–178. doi:10.2307/41410412

Venkatesh, V., and F. D. Davis. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science 46* (2), 186–204. doi:10.1287/mnsc.46.2.186.11926.

Yu, P., Wu, M.X., Yu, H., & Xiao, G.C. (2006). The Challenges for the Adoption of M-Health. *IEEE International Conference on Service Operations and Logistics and Informatics (SOLI 2006)*, Shanghai, China, June 21-23, 181-186. doi: 10.1109/SOLI.2006.329059.

Zhou, T., and H. Li. (2014). Understanding Mobile SNS Continuance Usage in China from the Perspectives of Social Influence and Privacy Concern. *Computers in Human Behavior* 37, 283–289.

Authors' Note

All correspondence should be addressed to:
Iga Rudawska
University of Szczecin
Mickiewicza 64, 71-101 Szczecin, Poland
iga.rudawska@usz.edu.pl

Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 20(1), May 2024, 131-154

GENERATIVE AI AS SOURCE OF CHANGE OF KNOWLEDGE MANAGEMENT PARADIGM

Dominika Kaczorowska-Spychalska
University of Lodz
Poland
ORCID 0000-0002-2566-0297

Nina Kotula
Kozminski University
Poland
ORCID 0000-0001-5089-0097

Grzegorz Mazurek
Kozminski University
Poland
ORCID 0000-0002-0047-6944

Łukasz Sułkowski
Jagiellonian University in Cracow
Poland
ORCID 0000-0002-1248-2743

The launch of ChatGPT in November 2022 revolutionized the accessibility of generative Artificial Intelligence, enabling conversational interactions. Extensively tested by millions, its influence on management has become a subject of debate. In the digital revolution, generative Artificial Intelligence possesses transformative potential, automates tasks, delivers novel goods and services, and generates valuable insights. However, challenges such as data quality, human oversight, and ethical considerations arise in the context of digital transformation. This research employs qualitative research methods to examine the current understanding of generative Artificial Intelligence and predict its influence on the knowledge management within organizations. By conducting a survey among industry experts, this paper aims to provide valuable insights into the integration of generative Artificial Intelligence and its implications for the knowledge management paradigm.

Keywords: *Knowledge Management, Generative AI, ChatGPT, Digital Transformation, Informaition and Communication Technologies*

DOI: https://doi.org/10.14254/1795-6889.2024.20-1.7

INTRODUCTION

Artificial intelligence (AI), increasingly, is naturally integrated into people's daily lives, finding an ever-widening spectrum of applications in products or services (Stoimenova & Price, 2020). It often goes unnoticed by users who are not aware of their interaction with AI (Steimer & Conick, 2018). Defined in a variety of ways, it focuses on a system's ability to correctly interpret data so that it learns from it and uses it to achieve specific goals and tasks through flexible adaptation (Kaplan & Haenlein, 2019). AI is described as a system capable of performing human tasks like making decisions or solving complex problems (Kar, 2016; Russell & Norvig, 1995), as well as making predictions about many phenomena and processes (Yang, 2022). By analyzing, for example, a person's facial expressions, the language they use, and the course of their interactions with them, AI systems can predict human needs (Gupta, 2017). AI, therefore, refers to programs, algorithms, systems, and machines that mimic human intelligence (Shankar, 2018) and exhibits a similar ability to mimic human responses (Shubhendu & Vijay, 2013).

As a multidisciplinary scientific field, encompassing robotics, neural networks, machine learning, image processing, and natural language processing, it has become a key component of digital transformation (Duan et al., 2019; Bilan et al., 2023) and one of the most important technologies forming the fourth industrial revolution (Schwab, 2016). Inspired by humans, it is different in practice. It has shifted the paradigm from an expert systems approach to one based on deep learning and big data (Mullainathan & Spiess, 2017). It has impacted our personal lives, but it has also fundamentally changed the way companies make decisions and interact with their internal and external stakeholders (Kaplan & Haenlein, 2019). Therefore, it should be developed to "respect, serve and protect people's physical and mental integrity, sense of personal and cultural identity and meet their basic needs" (AI HLEG, 2019)

Initially considered in terms of scientific research (Merrill & Schillebeeck, 2019), AI has now moved well beyond the realm of automation. The knowledge it possesses is repeatedly considered greater than that possessed by humans (Crawford & Calo, 2016), becoming a fundamental component of business growth (Markiewicz & Zheng, 2018). This emphasizes its importance in terms of business decision support. Recent developments in the development of AI are attributed to the significant growth in data volume and availability, the exponential increase in computing power, and the growth of increasingly complex and multifaceted statistical techniques' (Darwiche, 2018), which has accelerated the development of generative AI and its democratization processes.

Generative AI can be defined as an AI system, based on deep learning algorithms, that uses large data sets to create content and information that did not exist before (Nigram et al., 2021). Generative AI, unlike traditional artificial intelligence systems that are only able to analyze data and draw conclusions based on it, can also generate images, texts, graphics, paintings, and videos as if they were prepared by a human. More recently, it has also been granted copyright for its own soundtracks (Hewahi et al., 2019). In doing so, it can generate material with a highly realistic and consistent character (Sætra, 2022). Because of this, generative AI is an effective tool for businesses aiming to develop fresh, cutting-edge goods and services. However, generative AI is dependent on data and a data-based training process to generate new content (Terwiesch, 2023). This raises numerous questions about the actual level of creativity of the results of this work. At the same time, however, the notion of so-called artificial creativity interpreted as the ability of an AI system to *"achieve or simulate behaviors that would be considered creative in humans"* was already pointed out in 2018 (Wiggins & Forth, 2018). The emergence of generative artificial intelligence has highlighted the scale and scope of the potential further use of AI in various fields. Organizations are only just beginning to discover its real significance, especially in the context of building competitive advantage.

The multitude of generative AI tools currently available (e.g., ChatGPT, Bard, Midjourney, Dall-E2, Diffusion, or DreamUp), the announcement of more to come (Alibaba, Baidu, and Meta are talking about them), as well as the ever-expanding spectrum of functionalities they offer, arouse as much admiration as doubts, including in the context of knowledge management. Already hailed as a disruptive technology for many sectors and industries today (Haque et al., 2022), it nevertheless creates a few challenges for possible areas of uptake and implementation (idea, scope, goals, etc.), including in the evaluation of existing paradigms.

Although generative AI technology is developing rapidly, expanding the context and scale of its implementation (Helberger & Diakopoulos, 2023), it is still in its infancy (Haque et al., 2022), resulting in a large research gap. This article aims to provide a preliminary analysis of the current level of knowledge of this technology, with a prediction of its impact on knowledge management processes in organizations.

It seems that generative AI, like advanced technological tools, at earlier stages of human development (computer, internet, social media, or tablet, etc.) has the potential to be naturally accepted and adopted. However, this requires an awareness of what the technology is and how to use it in organizations effectively and efficiently.

LITERATURE REVIEW

Generative AI as a Catalyst of Digital Transition

When a new technology or business model enters the market and disturbs the status quo by offering a less complex, more affordable, and more readily available substitute for already available goods or services, this is known as a disruptive innovation (Christensen, 1997). Disruptive innovation's primary trait is its initial focus on niche markets underserved by current goods or services. When the disruptive technology or business model develops and becomes more popular, it eventually supplants existing goods and services (Christensen, 1997).

AI is emerging as a crucial technology that can assist firms in staying ahead of the curve in the age of digital transformation. As a ubiquitous technology, it is subject to continuous improvement and is becoming a contributor to further innovations (Brynjolfsson & McAfee, 2014; Bencsik, 2021). Considered a general-purpose technology and included in the so-called Big Four technologies (AI, Internet of Things, cloud, and mobility), it is recognized as one of the key pillars of digital transformation. When implemented into business models, it creates entirely new opportunities to scale them (Poniewierski, 2019). AI is not a separate and fragmented technology that develops in isolation and disconnected from market practice. On the one hand, it leads to modifications of existing models (e.g., adaptation versus total transformation), while on the other hand, it introduces completely new and different models from the ones we are used to. Nowadays, business perceives AI from the perspective of smarter products, smarter services, and increasingly automated processes. Unfortunately, there are still many companies trying to apply AI to outdated business strategies or inadequate processes (Marr, 2020).

The impact of the fourth industrial revolution on business has most often been seen as a shift from the simple digitalization that characterized the third industrial revolution, towards more complex and multifaceted forms of innovation, using an ecosystem of different technologies, including AI, in a different way than before (Schwab, 2016). This process is intensified by the emergence of generative AI, which can significantly influence the further course of digital transformation processes (dynamics, directions of change, perspectives, and level of complexity). It can revolutionize existing business models and implemented strategies, thanks to its unique potential. Because of this, generative AI is an effective tool for businesses aiming to develop fresh, cutting-edge goods and services.

In a business environment that is changing quickly, generative AI can, far more than before, improve organizational performance and give a competitive advantage by automating repetitive processes and producing new insights. For instance, generative AI can be applied to create new goods and services, automate customer support, and enhance corporate procedures (Chui et al., 2018).

As part of the digital transition, generative AI offers several important advantages, multiplying the benefits of using AI as such. The improvement in business processes is one advantage. With generative AI, routine operations such as data entry and annotation, for example, as well as report generation, document review, and analysis, may be automated, freeing staff to work on more strategic duties like innovation and client engagement (Merrill & Schillebeeck, 2019; Kedziora, 2022). Generative AI is also able, more than ever before, to take over the daily, tedious, and repetitive duties of employees (Burger et al., 2023), providing real support for them and allowing them to become more involved in more complex activities, including those of a creative or strategic nature.

The ability to make better decisions is another advantage of generative AI. Generative AI can help businesses make better-informed decisions, such as product development and market analysis, by creating fresh insights and predictions based on existing data (Agogino et al., 2020; Letkovsky et al., 2023). At the same time, it dramatically reduces the risk of human error, due, for example, to fatigue or distraction). It provides reproducible results, assuming comparable parameters (input data) (Wu et al., 2019). Also, the use of generative AI may open new economic prospects. Businesses can tap into new markets and acquire a competitive edge in a market that is changing quickly by utilizing generative AI to develop new goods and services (Mondejar et al., 2021), demand forecasting (Kolková & Ključnikov, 2022) as well as customer service. This will lead to a gradual transformation of different industries and market sectors, especially given that generative AI can create new data from existing data, rather than just analyzing it. The capabilities of generative AI are currently recognized as impressive and in many areas superior to current human capabilities.

Generative AI can therefore significantly support development if it is used in a legitimate, responsible, and ethical manner. However, it is important to be aware that the opposite is also possible, where AI-generated content is used indiscriminately, without respect for third-party rights, or for unwarranted purposes (Lim et al., 2023).

Even with the advantages, applying generative AI to the digital transition comes with several serious difficulties. The quality of the data is one issue. Organizations must ensure their data is correct, pertinent, and current since generative AI needs a lot of high-quality data to work correctly (Agogino et al., 2020). Unfortunately, generative AI does not always currently provide reliable and truthful information. It is also good at producing content that lacks any legitimate basis (Mollick & Mollick, 2022) or is laden with human biases, which increases its level of bias (Bender et al., 2021; Haluza & Jungwirth, 2023). This is because it does not have the typical ability to assess the reliability of the data (Sallam, 2023), as well as not always understand the meaning and essence of the words it processes (Gao et al., 2023), which further affects the credibility and reliability of the content and materials generated. It is also accused of having limited analytical and critical thinking capabilities (Rudolph et al., 2023). At the same time, it is worth noting that humans tend to take AI-generated information as persuasive and authoritative (Krügel et al., 2023; Zhou et al., 2020), and this can lead to over-reliance on this technology and intensify the process of perpetuating stereotypes or biases present in the data on which generative AI was trained. Like other AI models, those based on generative AI can collect and store data, which raises significant concerns about user privacy (Eliot, 2023) and cyber security. It also raises controversy about the level of creativity and the potential risk of copyright infringement if the generated material (text, graphics, images) resembles the original too closely (Karim, 2023). Moreover, because the results it generates are inexplicable (Bass, 2022), another difficulty is the need for humans to supervise things. Organizations must make sure that their algorithms are being trained on the relevant data and that the output is accurate because generative AI is only as good as the data it is trained on (Crawford & Calo, 2016). The use of generative AI raises ethical issues as well. For instance, generative AI can be employed to fabricate false information, assume the persona of another, and even produce deep fakes. It also raises questions in the dimension of the consequences of replacing human labor with systems based on generative AI. Companies must ensure that generative AI complies with ethical standards, laws, and social conventions. And while generative AI models generate several new challenges, this still definitely does not depreciate its potential to create novel content and materials (Audry, 2021).

The most well-known generative AI application is ChatGPT. It is a sizable language model that employs deep learning techniques to respond to natural language (NLP) inquiries that resemble those of humans - responses in a conversational model (Radford et al., 2019; van Dis et al., 2023). Launched by OpenAI on 30 November 2022, it has allowed the technology to be democratized, allowing people to interact with it in a conversational way. It has become the fastest-growing app reaching 100 million users within just two months of its launch (Hu, 2023). Its great strength is that instead of predicting or forecasting the correct or incorrect answer based on input, as AI has done so far, it generates its output based on its user's query, based on a trained model. Based on this, it combines words to form sentences and paragraphs based on what others have said on the topic, and its output takes on an innovative character, often also considered creative (Crawford et al., 2023). It uses large amounts of data, including those published in books, articles, and websites (Scharth, 2022), to first understand, and interpret user commands and questions and then generate optimal answers to them (Lund & Wang, 2023), which is important for evaluating its effectiveness (Kasneci et al., 2023). This is because it provides an opportunity to better understand the vocabulary relations of the language and the context in which they are embedded (Wang et al., 2023).

The versatility of ChatGPT, already at an early level of its development, is evident in its use in various applications. It generates human-like responses, in real-time, with the ability to adapt and scale them, to the actual expectations of users, which creates opportunities to be proactive with it and build on this to gain a market advantage. In doing so, however, it is worth noting that this process is not satisfactory enough in languages other than English (Bang et al., 2023).

Some essential characteristics of ChatGPT make it a potentially disruptive innovation, such as its capacity to learn from vast volumes of data and produce precise answers to intricate inquiries (Kaplan & Haenlein, 2019; Radford et al., 2019). Due to its capacity to deliver quicker and more accurate answers to business queries, it has the potential to be a revolutionary breakthrough in the management field.

The capacity of ChatGPT to democratize access to management insights is one of its main benefits. ChatGPT can be viewed and used by anybody with an internet connection, unlike conventional management systems that demand substantial training and expertise (Kaplan & Haenlein, 2019). Via the provision of a less expensive, less complicated, and more easily obtainable substitute for current goods and services, this has the potential to disrupt the market for management systems as it stands (Kaplan & Haenlein, 2019).

The capacity of ChatGPT to improve over time through continuous learning is another benefit. ChatGPT can increase its accuracy and efficacy by learning from a lot of data and user interactions, eventually replacing traditional management systems (Radford et al., 2019).

ChatGPT could significantly impact the field of management. ChatGPT can upend the current market and open fresh prospects for innovation by democratizing access to management insights and offering a less complex and more approachable substitute to conventional management systems (Kaplan & Haenlein, 2019). By offering a fresh stream of training data and enhancing the precision of business inquiries, ChatGPT can also improve the performance of current management systems (Radford et al., 2019). However, using ChatGPT also comes with several difficulties, such as the requirement to guarantee that the generated responses are impartial, truthful, and ethical (Zellers et al., 2019). Also, careful monitoring of ChatGPT deployment in management is required to prevent its users from replacing human workers.

In the digital revolution, generative AI has the potential to be a game-changer by delivering novel goods and services, automating repetitive processes, and producing fresh insights. Data quality, the necessity for human oversight, and ethical issues are only a few of the fundamental difficulties associated with employing generative AI in digital transformation. Businesses need to carefully analyze these issues and create plans that maximize the advantages of generative AI while lowering the hazards.

RQ 1. Does the use of generative AI create a competitive advantage for the organization?

RQ 2. What opportunities are created by the use of generative AI in an organization, including in the context of knowledge management?

RQ 3. What risks might arise from the use of generative AI in an organization, including in the context of knowledge management?

Paradigms for Knowledge Management

Knowledge management is crucial for organizations as it enables them to leverage their collective knowledge, promote innovation, and enhance decision-making processes (Earl, 2001; Boiko et al., 2021). The knowledge management paradigm in organizations significantly affects organizational performance, improving decision-making, productivity, and creativity; they can improve their competitiveness and obtain a sustained competitive advantage by successfully developing, capturing, and applying knowledge (Nonaka, 1994).

Several important theories have been developed in the field of knowledge management. The SECI Model, developed by Nonaka and Takeuchi (1995), describes the four modes of knowledge conversion: Socialization, Externalization, Combination, and Internalization. Socialization involves the sharing of tacit knowledge through direct interaction, while externalization is the process of articulating tacit knowledge into explicit forms. Combination refers to the integration of explicit knowledge, and internalization involves the assimilation of explicit knowledge into tacit knowledge. Generative AI impacts the SECI Model by enabling the automation of knowledge conversion processes. Through natural language processing and machine learning algorithms, AI can assist in capturing and codifying tacit knowledge (Brynjolfsson et al., 2023), facilitating the externalization and combination of knowledge. Additionally, AI-powered chatbots and virtual assistants can enhance socialization and internalization processes by providing personalized and context-specific knowledge support (Pavlik, 2023).

Polanyi's Tacit Knowledge Theory (1958) posits that there is a type of knowledge called "tacit knowledge" that is difficult to articulate explicitly but plays a significant role in practical expertise and decision-making. It emphasizes the idea that much of our knowledge is implicit, residing within individuals' minds and experiences. Effectively capturing and disseminating tacit knowledge, which is the knowledge that is challenging to codify and express, such as abilities, knowledge, and experience, is a challenge (Nonaka, 1994). Establishing a culture of openness and trust where staff members feel comfortable sharing their knowledge and skills is necessary for capturing and disseminating tacit knowledge (Grant, 1996).

AI affects Polanyi's Tacit Knowledge Theory (1958) by providing tools and algorithms that can analyze vast amounts of unstructured data (Dwivedi et al., 2023) and identify patterns or insights that may represent tacit knowledge (Brynjolfsson et al., 2023; Korzynski et al., 2023). Through machine learning and natural language processing, AI can help uncover hidden knowledge embedded within text, images, or audio, making it more accessible and facilitating its transfer and utilization within organizations.

Wenger's Communities of Practice theory suggests that learning and knowledge creation occur within social contexts where individuals with shared interests come together, interact, and develop a collective identity. These communities are groups of people who share a concern or a passion for something they do and learn how to do it better as they interact regularly to foster collaboration, knowledge sharing, and expertise development (Wenger, 1998).

AI affects Wenger's Communities of Practice theory by providing intelligent collaboration platforms and knowledge management systems that leverage natural language processing, machine learning, and data analytics. AI can facilitate the discovery of relevant communities, match individuals with similar interests, and recommend resources or experts within a community. AI-powered tools can also enhance knowledge sharing by providing personalized recommendations, answering questions, and facilitating interactions within communities (Paul et al., 2023). Overall, AI enhances the efficiency, accessibility, and connectivity of communities of practice.

Davenport and Prusak's Knowledge Management Enablers propose five key factors that support effective knowledge management within organizations: culture, technology, structure, measurement, and people (Davenport & Prusak, 1998). These enablers emphasize the importance of organizational culture, supportive technology infrastructure, appropriate structure, meaningful measurement metrics, and knowledgeable employees.

AI affects Davenport and Prusak's theory by offering advanced technologies that enhance each of these enablers. AI-powered systems can analyze and interpret organizational culture, identifying knowledge-sharing norms and facilitating a culture of collaboration. Through AI, organizations can leverage intelligent technologies and tools to capture, store, and disseminate knowledge more efficiently, thus improving technology enablers. AI algorithms can assist in structuring knowledge repositories, extracting relevant information, and providing personalized knowledge access (Arun Kumar et al., 2023; Guo et al., 2020). AI also plays a role in measurement by enabling the analysis of large datasets, identifying knowledge gaps, and evaluating the impact of knowledge management initiatives (Korzynski et al., 2023). Lastly, AI enhances the role of people by augmenting their expertise, providing intelligent recommendations, and enabling seamless collaboration across teams and individuals.

These theories provide frameworks for understanding and managing knowledge within organizations and generative AI has a profound impact on these theories by augmenting knowledge creation, capturing and codifying tacit knowledge, facilitating knowledge sharing and collaboration within communities, and enabling intelligent knowledge management systems. Generative AI technologies automate knowledge processes, analyze unstructured data, provide personalized recommendations, and enhance knowledge organization and measurement (Arun Kumar et al., 2023; Guo et al., 2020; Newman et al., 2022; Stuermer et al., 2017). The integration of generative AI into knowledge management practices has the potential to revolutionize how organizations create, share, and utilize knowledge.

Several knowledge management paradigms have been proposed over the years, each offering a different perspective on how knowledge should be managed within organizations. Codification Paradigm focuses on converting knowledge into explicit and codified forms that can be easily shared, stored, and accessed. It emphasizes the creation of knowledge repositories, databases, and documents to capture and disseminate knowledge throughout the organization. The codification paradigm often relies on technologies such as knowledge bases, intranets, and content management systems (Nonaka & Takeuchi, 1995). Personalization Paradigm emphasizes the tacit nature of knowledge and the importance of personal interactions (Nonaka & Toyama, 2015). It recognizes that knowledge often resides in the minds of individuals and is best shared through direct communication, socialization, and collaboration. This paradigm emphasizes the use of tools and platforms that facilitate knowledge sharing among employees, such as social networks, communities of practice, and collaborative tools (Nonaka & Toyama, 2015).

The social paradigm of knowledge management emphasizes the social nature of knowledge creation, sharing, and application. It recognizes that knowledge is embedded in social relationships, networks, and communities. This paradigm emphasizes the importance of fostering a culture of knowledge sharing, encouraging collaboration, and leveraging social technologies to facilitate knowledge exchange and co-creation (Wenger et al., 2002).

The networked paradigm views knowledge as a dynamic and interconnected system. It emphasizes the importance of building networks and relationships both within and outside the organization to access diverse sources of knowledge. This paradigm focuses on creating and leveraging networks, partnerships, alliances, and ecosystems to enhance knowledge sharing, learning, and innovation (Kimble et al., 2001; Oliinyk et al., 2021).

Knowledge Management with Generative AI

Knowledge management has become a crucial component of digital transformation strategies for firms looking to achieve a competitive advantage in the age of Industry 4.0. The process of developing, capturing, sharing, and using knowledge to improve organizational performance is known as knowledge management (Alavi & Leidner, 2001). In the field of knowledge management, AI has become a potent tool. Generative AI is one up-and-coming area of research. The potential for generative AI to alter the knowledge management paradigm is examined in this research.

AI systems, as mentioned earlier, that can produce new content, such as text, images, or music, based on data already present are referred to as generative AI systems. Instead of using rules and algorithms like standard AI, generative AI learns patterns from vast datasets and produces new content based on those patterns (Radford et al., 2021). Applications for generative AI range from chatbots to content generation to image and video synthesis.

Generative AI has the potential to significantly impact the knowledge management process in organizations. It can enhance various stages of the knowledge management cycle, including knowledge creation, capture, storage, organization, dissemination, and application. Generative AI can assist in knowledge creation by automatically generating new content, such as reports, articles, or even creative works. It can analyze large amounts of data, identify patterns, and generate insights or recommendations, augmenting the knowledge-creation process (Korzynski et al., 2023). Knowledge management rapidly uses AI to automate repetitive operations and extract insights from massive databases. Generative AI can facilitate knowledge capture by automatically extracting relevant information from various sources, such as documents, emails, or audio recordings. Generative AI has enormous promise, particularly in generating new information and insights from current data. It can identify key concepts, extract important details, and convert unstructured data into structured knowledge, making it easier to capture and store valuable information. Generative AI can improve knowledge storage by providing automated tagging, categorization, and indexing of knowledge assets. It can analyze the content, identify keywords, and assign appropriate metadata, making it easier to organize and retrieve knowledge when needed. Generative AI can support knowledge organization by clustering similar information, identifying relationships between different knowledge assets, and suggesting taxonomies or ontologies. It can help create knowledge maps, visualizations, or knowledge graphs, enabling better understanding and navigation of organizational knowledge. Generative AI can enhance knowledge dissemination by providing personalized and context-aware recommendations (Arun Kumar et al., 2023). It can analyze user preferences, behavior, and knowledge needs to deliver relevant content or expertise. Chatbots powered by generative AI can also assist in answering questions, providing on-demand information, and facilitating knowledge sharing within the organization. Finally, generative AI can augment knowledge application by assisting in decision-making processes. It can provide predictive analytics, simulate scenarios, or generate alternative solutions based on existing knowledge. By leveraging generative AI, organizations can make more informed decisions, optimize processes, and drive innovation. AI applications in knowledge management include decision support, social networking, expertise placement, and content management (Becerra-Fernandez & Sabherwal, 2014).

Generative AI can transform knowledge management completely by generating new information and insights from current data. It can create new knowledge to improve organizational performance by examining vast datasets to find patterns and links that may not be immediately obvious to humans. Moreover, generative AI can automate the production of fresh content, such as reports or presentations, saving employees' time and allowing them to concentrate on more imaginative and strategic activities. It can also provide personalized and context-aware recommendations (Arun Kumar et al., 2023).

Generative AI has a lot of potential to transform the knowledge management paradigm. Generative AI can transform knowledge management by extracting new knowledge and insights from current data, automating repetitive operations, and producing fresh and inventive goods and services. However, many things could be improved by using generative AI in knowledge management, such as the quality of the data, the requirement for human oversight, and ethical issues. Businesses need to carefully analyze these issues and create plans that maximize the advantages of generative AI while lowering the hazards. Generative AI can potentially be a potent tool for enhancing organizational performance and establishing a competitive edge in a market undergoing fast change.

This process should be considered from the point of view of the generative implications of AI and its impact on knowledge management processes at the societal level (macro level e.g. disinformation policy, manipulation, including unfair competitive struggle), on individual market sectors or groups of organizations (meso level – the takeover of human-created content within individual market sectors while marginalizing the role of the original creators), and on individual market actors considered on an individual basis (micro level – e.g. cognitive atrophy) (Sætra, 2022). This is influenced by both the characteristics of the technology (e.g., the convenience of use; the intuitiveness of solutions based on it; the security, including the security of data; the pleasure felt in using it), the characteristics of people using it (e.g., demographic characteristics, openness to the technology, subjective sense of effectiveness or perceived benefits, behavioral inertia), and situational factors directly accompanying the knowledge management and decision-making process.

Generative AI can influence management processes at three levels: strategic (e.g., data collection and analysis, facilitating the generation of suggestions that can guide evaluations), functional (e.g., improving customer service), and administrative (e.g., improving working time organization) (Korzynski et al., 2023). In doing so, it is worth noting the paradoxes described by Lim et al. (2023) related to the development of generative AI and its perception, which may significantly affect the further uptake of this technology at each of the levels mentioned:

- *"Generative AI is a 'friend' yet a 'foe'".*
- *Generative AI is 'capable' yet 'dependent'*
- *Generative AI is 'accessible' yet 'restrictive'*
- *Generative AI gets even 'popular' when 'banned'"*

This may lead to the formation of a new paradigm based on, different from existing, forms of collaboration and partnership between humans and artificial intelligence (Jarrahi et al., 2023; Zhou et al., 2020) (collaborative AI with model Human-in-the-Loop versus collaborative AI with model Human-out-of-the-Loop). This will be manifested in any form of co-creation based on both the integrated combination of human and technological creativity and the autonomous creativity of each party (Zhou et al., 2020) while considering their unique characteristics (specific only to them). The boundary of human substitutability for AI in knowledge creation and decision-making may therefore change (Shrestha et al., 2019). Understood in this way, the collaborative effect of human and generative AI requires mutual acceptance of each other's comments and suggestions, creating a space for each party in this interaction to interact more and more and reposition the technology in this process. It can therefore be assumed that generative AI, although it will naturally influence changes in the labor market, will at the same time not completely replace human labor, but rather be integrated with it. This will allow it to complement human decision-making processes rather than replace them (Agrawal et al., 2019). However, it is not obvious when the models for such collaboration and the associated subsequent paradigms will be shaped (Muller et al., 2022). Indeed, this requires an analysis of the potential scope of transformation regarding the necessary skills and competencies of employees and managers.

RQ 4. Which areas/functions of an organization's operations do generative AI appear to impact most strongly?

RQ 5. How do we implement generative AI into the organization's strategy, including in particular knowledge management strategy?

RQ 6. Does the effective and ethical use of generative IS require skills and competencies from employees/managers, especially in the sphere of knowledge management? If so, which ones?

RQ 7. Will the dynamics of collaboration between people in teams using generative AI change? Instead of 'wasting time' in meetings and (HLEG) exchange of ideas, will it be better to chat?

METHODS

The issue of the use of generative AI tools and models in the context of the Knowledge Management System has been the focus of Ritala (Ritala et al. 2024). An analysis of the level of use of ChatGPT (GenAI) in knowledge work was carried out to develop four ways in which knowledge workers interact with this technology. Mariani & Dwivedi (2024), on the other hand, analysed the importance of GenAI as a catalyst for innovation processes (research with leading innovation management researchers based on Delphi methodology). An analysis of the opportunities and challenges of using GenAI in the context of knowledge work (knowledge creation, knowledge storage, knowledge sharing and knowledge application) was conducted by Benbya H., Strich, F., & Tamm T. (2023). Using the Computer-Assisted Self-Interviewing technique we conducted 12 interviews: 11 with field experts from Poland and 1 with ChatGPT. Our human respondents were selected through purposive sampling techniques, based on their research and work experience. We invited female and male experts from Kozminski University and Jagiellonian University, and organizations such as DigitalPoland Foundation, Google, Humanities Institute and Deviniti. One of the experts invited to complete the survey questionnaire decided to do it anonymously, *see Table 1*.

Table 1. Characteristics of the respondents

Code	Gender	Position	Organization
R1	Male	Senior researcher	Kozminski University
R2	Female	Senior researcher	Kozminski University
R3	Male	Senior researcher	Jagiellonian University
R4	Male	Director	Humanities Institute
R5	Male	Director	DigitalPoland Foundation
R6	Female	Senior researcher	Jagiellonian University
R7	Male	Senior researcher	Kozminski University
R8	Male	Senior researcher	Jagiellonian University
R9	Female	Director	Google
R10	Male	Director	Deviniti
R11	Anonymous	Anonymous	Anonymous
ChatGPT	–	–	–

The survey questionnaire scenario was based on themes regarding knowledge management from the literature review. The survey questionnaire was prepared in the native language of participants, i.e., Polish, using the SurveyMonkey tool. The survey questionnaire scenario focused on the expert's thoughts regarding the opportunities and threats arising from the use of generative AI in the knowledge management sector.

The interviews were analyzed through dedicated software widely used by researchers to interpret qualitative data – MAXQDA 2020 software (Creswell, 2014). We used open coding, axial coding, and selective coding.

Following Dwivedi et al. (2023) discussion we stated our research question as follows:

RQ: Does generative AI challenge assumptions in knowledge management research and lead to a paradigm shift?

RESULTS

To understand the influence of generative AI on the knowledge management paradigm, we divided our findings into 4 sections. Each represents a different stage of the technology-powered knowledge management process in an organization (Alavi & Denford, 2012): knowledge creation process; knowledge storage and retrieval process; knowledge transfer and sharing process; knowledge application process.

Generative AI in knowledge management: knowledge creation process

The formation of new knowledge is recognized as an important and primary stage of knowledge management (Gurteen, 1998; Nonaka, 1994). Knowledge can be either created internally or obtained from the outside. According to our respondents, the ability to create knowledge is one of generative AI's advantages. Apart from recognizing the ability to create new knowledge quickly, our experts see the generative AI's potential to create new declarative knowledge, and so do researchers (Jarrahi et al., 2023).

"[Generative AI] Accelerates knowledge creation in the organization" (R5)

"[Generative AI] Can be used to create new knowledge, in particular: recognizing previously unknown patterns, searching organizational data, and discovering relationships, and developing new declarative knowledge." (R6)

Moreover, our respondents recognized cost-effectiveness of the knowledge created by generative AI.

> *"Acquiring knowledge is not as expensive in an organization as maintaining it. In my opinion, this is a great human-machine synergy that would work well in organizations that want to manage knowledge. In addition, a different approach to creating knowledge management systems, for example, to demand-driven, meaning an employee asks, and only AI produces that knowledge, rather than it having to be created manually by humans and stored just in case." (R10)*

As with generative AI decision support, our respondents stressed that the creative process also requires collaboration between humans and AI. Using generative AI tools in the creative process does not exempt people from creative thinking.

> *"Generative AI models can generate new ideas and solutions. Employees and managers must have the creativity to use these ideas and solutions in the knowledge management process." (R11)*

Generative AI's advanced ability to analyze data was recognized by our respondents. Hence the possibility of using the technology as a support in the creative process leading to the formation of new ideas, concepts, products, and innovations was mentioned. This goes in line with former research claiming that "ChatGPT can help people be more creative and productive and improve organizational knowledge management." (Dwivedi et al., 2023, p. 14)

> *"Generative AI can help automate and streamline business processes, improve product and service quality, and create new products and services. (...) Generative AI can help generate new ideas and solutions based on existing knowledge." (R11)*

Knowledge generated by generative AI may be too complex to understand and lead to internal chaos. Since generative AI technologies are still emerging (Kane, 2017), they are known for their tendency to hallucinate, i.e., create false information.

> *"I would see a major threat in a phenomenon that could be called the fictionalization of knowledge. It would involve the generation by AI of seemingly plausible scenarios or packages of structured information, which, however, upon deeper analysis, would turn out to be incompatible with reality. The big problem here would be a matter of scale: individual errors are easier to catch, but the situation becomes more complicated when they are, as it were, written into the DNA of the system." (R4)*

> *"Generative AI can generate very complex models and results that can be difficult to understand and control. In the event of errors or unexpected results, the organization can lose control of the knowledge-generation process. (...) Generative AI relies on algorithms and mathematical models, which can have limitations and be prone to error. The results generated by generative AI can be difficult to verify and confirm, which can introduce uncertainty into the knowledge management process" (GPT)*

Generative AI in knowledge management: knowledge storage and retrieval process

Our respondents indicated that generative AI technologies used in organizations aid their efficiency and productivity. As one of the advantages, the respondents mentioned the ability to structure stored knowledge so that it is easily accessible to recipients. Previous studies show that its particularly relevant at the organization's strategic level (Korzynski et al., 2023).

"Generative AI, in addition to its purely creative functions, can also have predictive qualities: it can help an organization make greater use of available information and process it into data useful for knowledge management." (R2)

"Generative AI models can help organize and categorize accumulated knowledge. They can also help create knowledge bases that allow for easier access to information and knowledge." (R11)

"AI can help organize accumulated knowledge by categorizing, tagging, and labeling data. This makes it easier for organizations to find the information they need later." (GPT)

Consistent with Korzynski et al. (2023), our respondents admit that the use of generative AI may result in managing tacit knowledge. Participants emphasized as follows:

"Generative AI can help uncover hidden knowledge in an organization, for example, by analyzing data from different sources and discovering hidden connections between them." (R11)

Among the opinions on efficiency and productivity, there were also concerns about the possible loss of knowledge in the organization. Daghfous et al. (2013, p. 655) indicate that "organizations should retain and diffuse architectural knowledge, improve strategic coordination among units, develop existing capabilities through different networking strategies and more effective networks, and transform these capabilities into effective organizational routines".

"Short-sighted decisions related to the apparent substitutability of human competence for AI can result in a significant loss of knowledge in organizations. AI in today's form is dyadic, while the functioning of organizations requires routines, multilateral, and multi-stakeholder. Those organizations that fail to recognize the dangers of replacing individual humans with AI will break the chain of routines and lose their existing competencies." (R3)

Generative AI in knowledge management: knowledge transfer and sharing process

Our respondents emphasized that generative AI allows sharing of knowledge within the organization and to society in general. This is consistent with Nguyen & Malik's (2022) results about the positive influence of AI on knowledge sharing in the hospitality industry.

"The use of generative AI can lead to several benefits in the knowledge management process, including: (...) wider distribution (popularization) of knowledge in the organization/society" (R7)

"Generative AI models can help create knowledge-sharing tools and systems, such as knowledge bases, knowledge portals, and collaboration systems." (R11)

The challenge of establishing a culture of openness and trust where employees share their knowledge was addressed as follows:

"[Generative AI] Eliminates common problems, such as reluctance to share knowledge." (R8)

While Arun Kumar et al. (2023) discussed the great influence of AI on the personalization of e-learning systems, our respondents emphasized the role of generative AI in adapting knowledge to employees' individual needs and abilities.

"Generative AI can help personalize employee learning by providing customized materials and training that meet each person's specific needs." (R11)

"The use of generative AI can lead to several benefits in the knowledge management process, including: (...) the ability to transform expert knowledge, into knowledge that is directly useful to a given employee in each position (e.g., selecting information, changing the form of information to one that is accessible (understandable) to a given employee" (R7)

Generative AI in knowledge management: knowledge application process

Researchers claim that generative AI systems may provide managerial recommendations if organizations implement the technology into their data management systems (Korzynski et al., 2023). The automation of data management and business processes was stated as follows:

"It [generative AI] seems to have the strongest potential to impact the ability to analyze large data sets, automate business processes (...) and improve strategic decision-making" (R6)

"Generative AI can help automate and streamline business processes, (...) It can also help analyze data, forecast trends and make business decisions." (R11)

Our respondents admit that generative AI tools support the decision-making process in organizations. Apart from the frequently emphasized ability to analyze big data and identify data trends that support the process itself, the participants stated the advantage of considerable time reduction of the process.

"AI will certainly have a significant impact on reducing knowledge management and decision-making time. What it should not significantly affect is certainly testing, which regardless of the information gained, input data and assumptions we should still perform." (R9)

"Generative AI can be used to generate guidance and suggestions that can help the decision-making process in an organization. This can be particularly useful in complex situations where quick and accurate decisions are needed." (GPT)

According to our experts and GPT at this stage of technological development human-AI collaboration in the knowledge management process is crucial which goes in line with recent research (Jarrahi et al., 2023). The role of human beings in an accurate decision-making process is still significant and the ability to analyze data and solutions provided by generative AI is an advantage.

"When redesigning processes, management should pay attention to sensitizing employees that unreflective reliance on AI alone can lead to mistakes. To counteract this, the organization can develop processes in which AI and humans make decisions in parallel and then compare results. Alternatively, the decision-making process can be sequential, so the employee confirms the decision made by the AI." (R6)

"The current technology is still a new tool for us, and the data analyzed is publicly available information that may not always be correct. Nevertheless, the ideal solution here is to obtain several possible solutions, and the human being should have the final say and the opportunity to make the final decision." (R9)

"Generative AI can provide a lot of information, but it is up to employees and management to know how to interpret and use it in the decision-making process. Therefore, employees must have analytical skills and know how to use the available analytical tools." (GPT)

Moreover, the participants recognize the decision-making and problem-solving supporting role of generative AI in the collaboration process – not necessarily from a strategic, managerial perspective.

"Generative AI models can be complementary in the collaboration process. They enable teams to process large amounts of data more quickly and efficiently, which can lead to better and more accurate decisions. In addition, generative AI can also help detect patterns and trends that may be difficult for humans to spot." (R11)

Simultaneously, the respondents admit that the AI-supported decision-making process comes with disadvantages such as difficulties understanding the process and its results or lack of reference to business realities.

"Decisions made by AI models are often based on complex algorithms that can be difficult for humans to understand. This makes it difficult to understand the decision-making process and analyze the results. (...) Generative AI models may be able to generate results that are technically correct but useless from a business perspective if context and business requirements are not considered." (R11)

Our respondents also expressed concern about the sensitive data of users and organizations. Yet another of the identified drawbacks of using generative AI in knowledge management is potential data leakage and cybersecurity threat.

"Generative AI may use user data and information inappropriately. As a result, there is a risk that this data may be inadvertently disclosed to external parties." (R2)

"Generative AI may require large amounts of data, including sensitive, personal data. There is a risk that this data may be used contrary to the organization's intentions or may be subject to privacy violations." (GPT)

DISCUSSION

In this paper, we examine the understanding of generative AI on the knowledge management and its possibility to shift the knowledge management paradigm. Prior research focusing on generative AI in knowledge management focused e.g., on influence of the technology on strategic, functional, and administrative level of management (Korzynski et al., 2023). Some other scholars investigated possible forms of collaboration and partnership between humans and AI (Jarrahi et al., 2023; Zhou et al., 2020).

This study supplements previous research by providing additional insights to the "perspective on organizations as knowledge systems and describes the four underlying knowledge management processes: knowledge creation, knowledge storage and retrieval, knowledge transfer, and knowledge application" (Alavi & Denford, 2012, p. 105) as for generative AI applications, including ChatGPT. A key finding of this study is that generative AI within organizations challenge the process of knowledge management, both internal and external, and impacts each of the four stages mentioned.

First, a deliberate use of generative AI in organization may provide competitive advantage and a unique opportunity to create a new knowledge in a cost-effective way and ability to analyze large sets of data. Generative AI based applications allow to support creativity and formation of new ideas, products, and services. Until recently activities and jobs which required creativity where perceived as “safe” one as opposed to repetitive work (Holford, 2019), yet the dissemination of generative AI represents a breakthrough and changes this concept of thinking (Holford, 2019; Torkington, 2023). Prior research discussed the ability of generative AI tools to “help people be more creative” (Dwivedi et al., 2023, p. 14), yet our findings show that tools such as ChatGPT can itself be creative and require the human-being supervision. Creativity researchers in their manifesto (Vinchon et al., 2023) underlined the role of human-AI collaboration, ethical and responsible use of the technology, that can help shape environment boosting human creativity and minimizing potential risks, such as technological unemployment.

Second, the role of generative AI in organization knowledge transfer and sharing is broad and very hopeful, incl. popularization of knowledge inside and outside organization, building culture of openness and personalizing it to individual needs. Scholars discussed the humans engagement in sharing their knowledge as a possibility to enhance generative AI-powered workplace (Tredinnick & Laybats, 2023). Nguyen and Malik (2022) discussed the positive role of AI systems enabling increased knowledge sharing that positively affects customer’s expedience with service quality.

Third, all advantages mentioned above go with threats. The most essential one from the perspective of knowledge management is the possibility to lose unique organizational data; create fake information; or provide difficulties for human to understand the processes related to knowledge management, supported by generative AI. These points are crucial to understand possible disadvantages related to utilization of generative AI applications within the organization. As discussed by Wach et al. (2023) there are multiple risks associated with use of generative AI in business, incl. lack of regulation, risk of multiple forms of disinformation generated by AI, possible leakage of sensitive data, and ethical challenges.

It also needs to be stressed that the authors of this paper are aware of the limitations of the research findings. The study is one of the initial contributions to the discussion of generative AI in knowledge management and focuses only on opinion given by experts from Poland. Therefore, additional studies in other contexts, with experts from experts from less and more technologically advanced countries should be conducted. Moreover, the technological environment changes rapidly and, as mentioned by one of our respondents, “the answers to the questions for this article the ones I started providing last week needed to be updated” (R9). Therefore, the results of our study may not be very valid after its publication and even greater technological advancement and understanding of generative AI and its influence on the knowledge management paradigm.

Future research on the topic of generative AI in knowledge management paradigm should consider advantages and disadvantages related to the use of the technology in organizations separately, with more detailed perspective. Futhermore, we propose that future research closely and individually examine the influence of generative AI on different stages of the knowledge management process within the organization.

CONCLUSIONS

The article discusses the current level of knowledge of generative AI, with a prediction of its impact on knowledge management processes in organizations. Generative AI uses deep learning algorithms to create new content, which can help businesses develop fresh, cutting-edge goods and services. Generative AI can also automate repetitive processes, produce new insights, accumulate knowledge, and assist in making better-informed decisions. Moreover, the use of generative AI in organizations can address the challenge of managing tacit knowledge and the internal reluctance to share knowledge. Despite the advantages, applying generative AI to the knowledge management process comes with several serious difficulties and threats. Organizations must ensure that their data is correct, relevant, and current. They must also ensure that their algorithms are being trained on the relevant data and that the output is accurate. The use of generative AI requires employees and managers to understand the technology and have the analytical competence to verify the results obtained. Furthermore, the use of generative AI raises ethical issues such as the fabrication of false information, deep fakes, and impersonation. From the perspective of the knowledge management process, this phenomenon is particularly dangerous and can lead to chaos within the organization and/or loss of organizational knowledge. Companies must ensure that generative AI complies with ethical standards, laws, and social conventions. In addition, to ensure the continuity of the knowledge management process, employees and managers should be aware of the challenges posed by using generative AI. Learning how humans and AI work together seems inevitable.

One of the most well-known AI applications is ChatGPT, a sizable language model that employs deep learning techniques to respond to natural language inquiries. ChatGPT has the potential to democratize access to management insights and offer a less complex and more approachable substitute for conventional management systems. It can improve over time through continuous learning and can eventually replace traditional management systems. However, the use of ChatGPT also comes with difficulties, such as ensuring that the generated responses are impartial, truthful, and ethical, and preventing its users from replacing human workers.

According to our study results, all the stages of the knowledge-management process may be influenced by generative AI technologies. The process of human-AI knowledge co-creation and co-management requires a new approach to the knowledge-management paradigm. An effective collaborative AI process is essential, ensuring that generative AI is integrated into existing knowledge management workflows, allowing for seamless collaboration and knowledge sharing. While generative AI tools automate certain aspects of knowledge management, they do not eliminate the role of interpersonal networks and connections. Instead, they can complement and enhance these networks by facilitating more efficient information exchange and expanding the reach and accessibility of knowledge within networks. This arises a further need to explore the phenomena.

Through the mass adoption of generative AI tools among users, interpersonal networks and connections can become even more relevant. These tools can amplify the ability to connect with relevant expertise, foster communities of practice, and enable broader knowledge dissemination. The combination of generative AI and interpersonal networks can create a synergistic effect, leveraging the strengths of both to enhance knowledge sharing and collaboration within organizations.

In conclusion, generative AI has the potential to significantly impact digital transformation, but its application comes with serious difficulties, including the need for high-quality data, algorithmic accuracy, and ethical considerations. The democratization of access to management insights and the ability to improve over time through continuous learning are two significant benefits of ChatGPT. However, the use of ChatGPT also requires careful monitoring to prevent the replacement of human workers and ensure impartial, truthful, and ethical responses. As the digital revolution continues, organizations must consider the potential benefits and difficulties of generative AI carefully.

The successful use of generative AI in knowledge management is determined by a combination of factors. Organizational culture plays a significant role as it needs to foster a learning and innovation mindset that embraces the integration of AI technologies. The digital competence of participants is crucial to effectively utilize and leverage generative AI tools and platforms.

IMPLICATIONS FOR RESEARCH AND APPLICATION

Research described in this paper provides a preliminary analysis of the current level of knowledge and understanding of generative AI, with a prediction of its impact on knowledge management processes in organizations.

From the practical point of view, our study results can guide managers and organizations in understangding the challenges affiliated with implementation generative AI applications and its possible influence on the company's knowledge management. This is extremely important from the business perspective in challenging times of digital transformation and technological race, which, properly implemented, can be a source of competitive advantage.

REFERENCES

Agogino, A. M., Mattingly, S. P., & Hmelo-Silver, C. E. (2020). Empowering Innovation: Artificial Intelligence and Generative Design. *Proceedings of the 2020 ASEE Virtual Annual Conference Content Access*, 1-16. https://doi.org/https://doi.org/10.3389/frai.2020.583194

Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. *Journal of Economic Perspectives*, *33*(2), 31-50. https://doi.org/10.1257/jep.33.2.31

Alavi, M., & Denford, J. S. (2012). Knowledge Management: Process, Practice, and Web 2.0. In *Handbook of Organizational Learning and Knowledge Management* (pp. 105-124). https://doi.org/https://doi.org/10.1002/9781119207245.ch6

Alavi, M., & Leidner, D. E. (2001). Review: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. *MIS Quarterly*, *25*(1), 107-136. https://doi.org/10.2307/3250961

Arun Kumar, U., Mahendran, G., & Gobhinath, S. (2023, 2023//). A Review on Artificial Intelligence Based E-Learning System. Pervasive Computing and Social Networking, Singapore.

Audry, S. (2021). *Art in the Age of Machine Learning*. The MIT Press.

Bang, Y., Cahyawijaya, S., Lee, N., Dai, W., Su, D., Wilie, B., Lovenia, H., Ji, Z., Yu, T., Chung, W., Do, Q., Yan, X., & Fung, P. (2023). *A Multitask, Multilingual, Multimodal Evaluation of ChatGPT on Reasoning, Hallucination, and Interactivity* arXiv preprint. https://doi.org/10.48550/arXiv.2302.04023

Bass, D. (2022). OpenAI Chatbot So Good It Can Fool Humans, Even When It's Wrong. https://www.bloomberg.com/news/articles/2022-12-07/openai-chatbot-so-good-it-can-fool-humans-even-when-it-s-wrong#xj4y7vzkg

Becerra-Fernandez, I., & Sabherwal, R. (2014). *Knowledge Management: Systems and Processes*. Taylor & Francis.
Bencsik, A. (2021). The sixth generation of knowledge management – the headway of artificial intelligence. *Journal of International Studies, 14*(2), 84-101. doi:10.14254/2071-8330.2021/14-2/6
Benbya, H., Strich, F., Tamm, T. (2024). Navigating Generative Artificial Intelligence Promises and Perils for Knowledge and Creative Work. *Journal of the Association for Information Systems, 25*(1), 23-36. https:doi.org/10.17705/1jais.00861
Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). *On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?* Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, Virtual Event, Canada. https://doi.org/10.1145/3442188.3445922
Bilan, Y., Oliinyk, O., Mishchuk, H., & Skare, M. (2023). Impact of information and communications technology on the development and use of knowledge. *Technological Forecasting and Social Change, 191*, 122519. DOI: 10.1016/j.techfore.2023.122519
Boiko, A., Zwolińska-Ligaj, M., Bozhenko, V., Florczak, E., & Ovcharenko, V. (2021). Readiness for implementing innovations in banking in advanced and emerging economies. *Journal of International Studies, 14*(4), 236-250. doi:10.14254/2071-8330.2021/14-4/16
Brynjolfsson, E., Li, D., & Raymond, L. (2023). Generative AI at Work [NBER Working Paper No. w31161]. https://doi.org/https://dx.doi.org/10.2139/ssrn.4426942
Brynjolfsson, E., & McAfee, A. (2014). *The Second Machine Age - Work, Progress, and Prosperity in a Time of Brilliant Technologies*. WW Norton & Company.
Burger, B., Kanbach, D. K., Kraus, S., Breier, M., & Corvello, V. (2023). On the use of AI-based tools like ChatGPT to support management research. *European Journal of Innovation Management*, *26*(7), 233-241. https://doi.org/10.1108/EJIM-02-2023-0156
Christensen, C. M. (1997). *The innovator's dilemma: When new technologies cause great firms to fail*. Harvard Business School Press.
Chui, M., Manyika, J., & Miremadi, M. (2018). What AI can and can't do (yet) for your business. *McKinsey Quarterly*. https://www.mckinsey.com/capabilities/quantumblack/our-insights/what-ai-can-and-cant-do-yet-for-your-business#/
Crawford, J., Cowling, M., & Allen, K.-A. (2023). Leadership is needed for ethical ChatGPT: Character, assessment, and learning using artificial intelligence (AI). *Journal of University Teaching and Learning Practice, 20*. https://doi.org/10.53761/1.20.3.02
Crawford, K., & Calo, R. (2016). There is a blind spot in AI research. *Nature*, *538*(7625), 311-313. https://doi.org/10.1038/538311a
Creswell, J. W. (2014). *Research design: qualitative, quantitative and mixed methods approaches* (V. Knight, Ed. 4 ed.). SAGE Publications, Inc. https://fe.unj.ac.id/wp-content/uploads/2019/08/Research-Design_Qualitative-Quantitative-and-Mixed-Methods-Approaches.pdf
Daghfous, A., Belkhodja, O., & C. Angell, L. (2013). Understanding and managing knowledge loss. *Journal of Knowledge Management*, *17*(5), 639-660. https://doi.org/10.1108/JKM-12-2012-0394
Darwiche, A. (2018). Human-level intelligence or animal-like abilities? *Commun. ACM*, *61*(10), 56–67. https://doi.org/10.1145/3271625
Davenport, T., & Prusak, L. (1998). *Working Knowledge: How Organizations Manage What They Know* (Vol. 1). https://doi.org/10.1145/348772.348775
Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63-71. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2019.01.021
Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., . . . Wright, R. (2023). Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2023.102642
Earl, M. (2001). Knowledge Management Strategies: Toward a Taxonomy. *Journal of Management Information Systems*, *18*(1), 215-233. http://www.jstor.org/stable/40398522

Eliot, L. (2023). Generative AI ChatGPT Can Disturbingly Gobble Up Your Private And Confidential Data, Forewarns AI Ethics And AI Law. *January 27, 2023*. https://www.forbes.com/sites/lanceeliot/2023/01/27/generative-ai-chatgpt-can-disturbingly-gobble-up-your-private-and-confidential-data-forewarns-ai-ethics-and-ai-law/?sh=6e67a2d17fdb

Gao, J., Zhao, H., Yu, C., & Xu, R. (2023). *Exploring the Feasibility of ChatGPT for Event Extraction*.

Grant, R. M. (1996). Prospering in Dynamically-Competitive Environments: Organizational Capability as Knowledge Integration. *Organization Science*, *7*(4), 375-387. https://doi.org/10.1287/orsc.7.4.375

Guo, J., Fan, Y., Pang, L., Yang, L., Ai, Q., Zamani, H., Wu, C., Croft, W. B., & Cheng, X. (2020). A Deep Look into neural ranking models for information retrieval. *Information Processing & Management*, *57*(6), 102067. https://doi.org/https://doi.org/10.1016/j.ipm.2019.102067

Gupta, N. (2017). A Literature Survey on Artificial Intelligence. *International Journal of Engineering Research & Technology (Ijert)*, *5*(19). 1-5.

Gurteen, D. (1998). Knowledge, Creativity and Innovation. *Journal of Knowledge Management*, *2*(1), 5-13. https://doi.org/10.1108/13673279810800744

Haluza, D., & Jungwirth, D. (2023). Artificial Intelligence and Ten Societal Megatrends: An Exploratory Study Using GPT-3. *Systems*, *11*(3), 120. https://www.mdpi.com/2079-8954/11/3/120

Haque, M. U., Dharmadasa, I., Sworna, Z. T., Rajapakse, R., & Ahmad, H. (2022). *"I think this is the most disruptive technology": Exploring Sentiments of ChatGPT Early Adopters using Twitter Data*. https://doi.org/10.48550/arXiv.2212.05856

Helberger, N., & Diakopoulos, N. (2023). ChatGPT and the AI Act. *Internet Policy Review*, *12*(1). https://doi.org/https://doi.org/10.14763/2023.1.1682

Hewahi, N., AlSaigal, S., & AlJanahi, S. (2019). Generation of music pieces using machine learning: long short-term memory neural networks approach. *Arab Journal of Basic and Applied Sciences*, *26*(1), 397-413. https://doi.org/10.1080/25765299.2019.1649972

HLEG, A. (2019). *A definition of AI: Main capabilities and scientific disciplines*. Brussels: European Commission Retrieved from https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

Holford, W. D. (2019). The future of human creative knowledge work within the digital economy. *Futures*, *105*, 143-154. https://doi.org/https://doi.org/10.1016/j.futures.2018.10.002

Hu, K. (2023). https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01 https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/

Jarrahi, M. H., Askay, D., Eshraghi, A., & Smith, P. (2023). Artificial intelligence and knowledge management: A partnership between human and AI. *Business Horizons*, *66*(1), 87-99. https://doi.org/https://doi.org/10.1016/j.bushor.2022.03.002

Kane, G. C. (2017). The evolutionary implications of social media for organizational knowledge management. *Information and Organization*, *27*(1), 37-46. https://doi.org/https://doi.org/10.1016/j.infoandorg.2017.01.001

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15-25. https://doi.org/https://doi.org/10.1016/j.bushor.2018.08.004

Kar, A. K. (2016). Bio inspired computing – A review of algorithms and scope of applications. *Expert Systems with Applications*, *59*, 20-32. https://doi.org/https://doi.org/10.1016/j.eswa.2016.04.018

Karim, R. (2023). ChatGPT: Old AI problems in a new guise, new problems in disguise. https://lens.monash.edu/@politics-society/2023/02/13/1385448/chatgpt-old-ai-problems-in-a-new-guise-new-problems-in-disguise

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., . . . Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274. https://doi.org/https://doi.org/10.1016/j.lindif.2023.102274

Kedziora, D. (2022). Botsourcing, Roboshoring or Virtual Backoffice? Perspectives on Implementing Robotic Process Automation (RPA) and Artificial Intelligence (AI). *Human Technology*, *18*(2), 92–97. https://doi.org/10.14254/1795-6889.2022.18-2.1

Kimble, C., Hildreth, P., & Wright, P. (2001). Communities of Practice: Going Virtual. In Y. Malhotra (Ed.), *Knowledge Management and Business Model Innovation* (pp. 216-230). IGI Global. https://doi.org/10.4018/978-1-878289-98-8.ch013

Kolková, A., & Ključnikov, A. (2022). Demand forecasting: AI-based, statistical and hybrid models vs practice-based models - the case of SMEs and large enterprises. *Economics and Sociology, 15*(4), 39-62. doi:10.14254/2071789X.2022/15-4/2

Korzynski, P., Mazurek, G., Altmann, A., Ejdys, J., Kazlauskaite, R., Paliszkiewicz, J., Wach, K., & Ziemba, E. (2023). Generative artificial intelligence as a new context for management theories: analysis of ChatGPT. *Central European Management Journal*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/CEMJ-02-2023-0091

Krügel, S., Ostermaier, A., & Uhl, M. (2023). *The moral authority of ChatGPT* arXiv preprint https://doi.org/10.48550/arXiv.2301.07098

Letkovsky, S., Jencova, S., Vasanicova, P., Gavura, S., & Bacik, R. (2023). Predicting bankruptcy using artificial intelligence: The case of the engineering industry. *Economics and Sociology, 16*(4), 178-190. doi:10.14254/2071789X.2023/16-4/8

Lim, W. M., Gunasekara, A., Pallant, J. L., Pallant, J. I., & Pechenkina, E. (2023). Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators. *The International Journal of Management Education*, *21*(2), 100790. https://doi.org/https://doi.org/10.1016/j.ijme.2023.100790

Lund, B. D., & Wang, T. (2023). Chatting about ChatGPT: how may AI and GPT impact academia and libraries? *Library Hi Tech News*, *40*(3), 26-29. https://doi.org/10.1108/LHTN-01-2023-0009

Markiewicz, T., & Zheng, J. (2018). *Getting Started with Artificial Intelligence. A Practical Guide to Building Enterprise Applications*. O'Reilly.

Marr, B. (2020). *The Intelligence Revolution. Transforming your business with AI*. Kogan Page.

Mariani, M., Dwivedi, Y. (2024). Generative artificial intelligence in innovation management: A preview of future research developments. *Journal of Business Research, 175*, 114542. https://doi.org/10.1016/j.jbusres.2024.114542

Merrill, R. K., & Schillebeeck, S. J. (2019). *SUSTAINABLE DIGITAL FINANCE IN ASIA: Creating Environmental Impact through Bank Transformation*. https://www.dbs.com/iwov-resources/images/sustainability/reports/Sustainable%20Digital%20Finance%20in%20Asia_FINAL_22.pdf

Mollick, E. R., & Mollick, L. (2022). *New Modes of Learning Enabled by AI Chatbots: Three Methods and Assignments*.

Mondejar, M. E., Avtar, R., Diaz, H. L. B., Dubey, R. K., Esteban, J., Gómez-Morales, A., Hallam, B., Mbungu, N. T., Okolo, C. C., Prasad, K. A., She, Q., & Garcia-Segura, S. (2021). Digitalization to achieve sustainable development goals: Steps towards a Smart Green Planet. *Science of The Total Environment*, *794*, 148539. https://doi.org/https://doi.org/10.1016/j.scitotenv.2021.148539

Mullainathan, S., & Spiess, J. (2017). Machine Learning: An Applied Econometric Approach. *The Journal of Economic Perspectives*, *31*(2), 87-106. http://www.jstor.org/stable/44235000

Muller, M., Chilton, L. B., Kantosalo, A., Martin, C. P., & Walsh, G. (2022). *GenAICHI: Generative AI and HCI* Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems, New Orleans, LA, USA. https://doi.org/10.1145/3491101.3503719

Newman, J., Mintrom, M., & O'Neill, D. (2022). Digital technologies, artificial intelligence, and bureaucratic transformation. *Futures*, *136*, 102886. https://doi.org/https://doi.org/10.1016/j.futures.2021.102886

Nguyen, T.-M., & Malik, A. (2022). A Two-Wave Cross-Lagged Study on AI Service Quality: The Moderating Effects of the Job Level and Job Role. *British Journal of Management*, *33*(3), 1221-1237. https://doi.org/https://doi.org/10.1111/1467-8551.12540

Nonaka, I. (1994). A Dynamic Theory of Organizational Knowledge Creation. *Organization Science*, *5*(1), 14-37. https://doi.org/10.1287/orsc.5.1.14

Nonaka, I., & Takeuchi, H. (1995). *The Knowledge-creating Company: How Japanese Companies Create the Dynamics of Innovation*. Oxford University Press.

Nonaka, I., & Toyama, R. (2015). The Knowledge-creating Theory Revisited: Knowledge Creation as a Synthesizing Process. In J. S. Edwards (Ed.), *The Essentials of Knowledge Management* (pp. 95-110). Palgrave Macmillan UK. https://doi.org/10.1057/9781137552105_4

Oliinyk, O., Bilan, Y., & Mishchuk, H. (2021). Knowledge Management and Economic Growth: The Assessment of Links and Determinants of Regulation. *Central European Management Journal*, *29*(3), 20-39. https://doi.org/10.7206/cemj.2658-0845.52

Paul, J., Ueno, A., & Dennis, C. (2023). ChatGPT and consumers: Benefits, Pitfalls and Future Research Agenda. *International Journal of Consumer Studies*, *47*(4), 1213-1225. https://doi.org/https://doi.org/10.1111/ijcs.12928

Pavlik, J. V. (2023). Collaborating With ChatGPT: Considering the Implications of Generative Artificial Intelligence for Journalism and Media Education. *Journalism & Mass Communication Educator*, *78*(1), 84-93. https://doi.org/10.1177/10776958221149577

Polanyi, M. (1958). *Personal Knowledge: Towards a Post-Critical Philosophy* (Vol. 20). University of Chicago Press.

Poniewierski, A. (2019). *SPEED no limits in the digital era*.

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language Models are Unsupervised Multitask Learners. *1*(8), 1-17. https://d4mucfpksywv.cloudfront.net/better-language-models/language-models.pdf

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2021). *Language models are few-shot learners* https://d4mucfpksywv.cloudfront.net/better-language-models/language_models_are_unsupervised_multitask_learners.pdf

Ritala, P., Ruokonen, M, Ramaul, L. (2024). Transforming boundaries: how does ChatGPT change knowledge work?. *Journal of Business Strategy, 45*(3), 214-220. https://doi.org/10.1108/JBS-05-2023-0094

Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education? *Journal of Applied Learning & Teaching*, *6*(1). https://doi.org/https://doi.org/10.37074/jalt.2023.6.1.9

Russell, S., & Norvig, P. (1995). *A modern approach. Artificial Intelligence*.

Sætra, H. (2022). *Generative AI: Here to stay, but for good?* https://doi.org/10.2139/ssrn.4315686

Sallam, M. (2023). The Utility of ChatGPT as an Example of Large Language Models in Healthcare Education, Research and Practice: Systematic Review on the Future Perspectives and Potential Limitations. *medRxiv*, 2023.2002.2019.23286155. https://doi.org/10.1101/2023.02.19.23286155

Scharth, M. (2022). The ChatGPT chatbot is blowing people away with its writing skills. https://www.sydney.edu.au/news-opinion/news/2022/12/08/the-chatgpt-chatbot-is-blowing-people-away-with-its-writing-skil.html

Schwab, K. (2016). The Fourth Industrial Revolution: what it means, how to respond. Retrieved 10/05/2021, from https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/

Shankar, V. (2018). How Artificial Intelligence (AI) is Reshaping Retailing. *Journal of Retailing*, *94*(4), vi-xi. https://doi.org/https://doi.org/10.1016/S0022-4359(18)30076-9

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational Decision-Making Structures in the Age of Artificial Intelligence. *California Management Review*, *61*(4), 66-83. https://doi.org/10.1177/0008125619862257

Shubhendu, S., & Vijay, J. F. (2013). Applicability of Artificial Intelligence in Different Fields of Life.

Steimer, S., & Conick, H. (2018). *What Does the Future of Customer Experience Look Like?* Retrieved May 05 from https://www.ama.org/marketing-news/what-does-the-future-of-customer-experience-look-like/

Stoimenova, N., & Price, R. (2020). Exploring the Nuances of Designing (with/for) Artificial Intelligence. *Design Issues*, *36*(4), 45-55. https://doi.org/10.1162/desi_a_00613

Stuermer, M., Abu-Tayeh, G., & Myrach, T. (2017). Digital sustainability: basic conditions for sustainable digital artifacts and their ecosystems. *Sustainability Science*, *12*(2), 247-262. https://doi.org/10.1007/s11625-016-0412-2

Terwiesch, C. (2023). Would Chat GPT3 Get a Wharton MBA? A Prediction Based on Its Performance in the Operations Management Course. https://mackinstitute.wharton.upenn.edu/wp-content/uploads/2023/01/Christian-Terwiesch-Chat-GTP.pdf

Torkington, S. (2023). How might generative AI change creative jobs? *GROWTH2023*. Retrieved June 28, 2023, from https://www.weforum.org/agenda/2023/05/generative-ai-creative-jobs/

Tredinnick, L., & Laybats, C. (2023). The dangers of generative artificial intelligence. *Business Information Review*. https://doi.org/https://doi.org/10.1177_02663821231183756 van Dis, E. A. M., Bollen, J., Zuidema, W., van Rooij, R., & Bockting, C. L. (2023). ChatGPT: five priorities for research. *Nature*, *614*(7947), 224-226. https://doi.org/10.1038/d41586-023-00288-7

Vinchon, F., Lubart, T., Bartolotta, S., Gironnay, V., Botella, M., Bourgeois-Bougrine, S., Burkhardt, J.-M., Bonnardel, N., Corazza, G. E., Glăveanu, V., Hanchett Hanson, M., Ivcevic, Z., Karwowski, M., Kaufman, J. C., Okada, T., Reiter-Palmon, R., & Gaggioli, A. (2023). Artificial Intelligence & Creativity: A Manifesto for Collaboration. *The Journal of Creative Behavior*, *n/a*(n/a). https://doi.org/https://doi.org/10.1002/jocb.597

Wach, K., Ejdys, J., Kazlauskaite, R., Korzynski, P., Mazurek, G., Paliszkiewicz, J., Ziemba, E., & Duong, D. (2023). The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. *Entrepreneurial Business and Economics Review*, *11*, 7-24. https://doi.org/10.15678/EBER.2023.110201

Wang, F. Y., Miao, Q., Li, X., Wang, X., & Lin, Y. (2023). What Does ChatGPT Say: The DAO from Algorithmic Intelligence to Linguistic Intelligence. *IEEE/CAA Journal of Automatica Sinica*, *10*(3), 575-579. https://doi.org/10.1109/JAS.2023.123486

Wenger, E. (1998). *Communities of Practice: Learning, Meaning, and Identity*. Cambridge University Press. https://doi.org/DOI: 10.1017/CBO9780511803932

Wenger, E., McDermott, R. A., & Snyder, W. (2002). *Cultivating Communities of Practice: A Guide to Managing Knowledge*. Harvard Business School Press.

Wiggins, G. A., & Forth, J. (2018). 267Computational Creativity and Live Algorithms. In R. T. Dean & A. McLean (Eds.), *The Oxford Handbook of Algorithmic Music* (pp. 0). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190226992.013.0019

Wu, A., Nowozin, S., Meeds, E., Turner, R. E., Hernández-Lobato, J. M., & Gaunt, A. L. (2019). *Deterministic Variational Inference for Robust Bayesian Neural Networks* https://openreview.net/forum?id=B1l08oAct7

Yang, W. (2022). Artificial Intelligence education for young children: Why, what, and how in curriculum design and implementation. *Computers and Education: Artificial Intelligence*, *3*, 100061. https://doi.org/https://doi.org/10.1016/j.caeai.2022.100061

Zellers, R., Holtzman, A., Rashkin, H., Bisk, Y., Farhadi, A., Roesner, F., & Choi, Y. (2019). Defending against neural fake news. In *Proceedings of the 33rd International Conference on Neural Information Processing Systems* (pp. Article 812). Curran Associates Inc.

Zhou, Y., Koyama, Y., Goto, M., & Igarashi, T. (2020). *Generative Melody Composition with Human-in-the-Loop Bayesian Optimization* arXiv preprint. https://doi.org/https://doi.org/10.48550/arXiv.2010.03190

All correspondence should be addressed to

Dominika Kaczorowska-Spychalska
Department of Marketing, Faculty of Management,
University of Lodz, Poland
e-mail: dominika.spychalska@uni.lodz.pl
ORCID: 0000-0002-2566-0297

Nina Kotula
Kozminski University, Poland
e-mail: nkotula@kozminski.edu.pl
ORCID: 0000-0001-5089-0097

Grzegorz Mazurek
Department of Marketing,
Kozminski University, Poland
e-mail: gmazurek@kozminski.edu.pl
ORCID: 0000-0002-0047-6944

Łukasz Sułkowski
Institute of Public Affairs,
Jagiellonian University in Cracow, Poland
e-mail: lukasz.sulkowski@uj.edu.pl
ORCID: 0000-0002-1248-2743

Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 20(1), May 2024, 155-177

SOCIAL ACCEPTANCE OF ARTIFICIAL INTELLIGENCE (AI) APPLICATION FOR IMPROVING MEDICAL SERVICE DIAGNOSTICS

Joanna Ejdys
Bialystok University of Technology
Faculty of Engineering Management
Poland
ORCID 0000-0002-5132-166X

Magdalena Czerwińska
Lublin University of Technology
Faculty of Management
Poland
ORCID 0000-0002-7945-1044

Romualdas Ginevičius
Mykolas Romeris University
Lithuania
ORCID 0000-0003-2067-4398

Abstract: *The aim of the conducted research was to assess the attitude of the Polish society towards the use of artificial intelligence in medical diagnostics. In the research process, we sought answers to three research questions: how trust in the use of AI for medical diagnostics can be measured; if societal openness to technology determines trust in the use of AI for medical diagnostics purposes; and if a higher level of trust in the use of AI for medical diagnostics influences the potential improvement in the quality of medical diagnostics as perceived by Poles. The authors' particular focus was on the following three constructs and the relationships between them: openness to new technologies (OP), willingness to trust AI in medical diagnostics (T), and perceived impact of AI application on the quality of medical diagnostic services (PI). A survey was conducted on a representative sample of 1063 Polish respondents to seek answers to the above questions. The survey was conducted using the CATI technique.*

Keywords: *artificial intelligence, medical diagnostics, trust to AI, medical diagnostics quality.*

DOI: https://doi.org/10.14254/1795-6889.2024.20-1.8

INTRODUCTION

Global socio-economic development trends pose diverse and complex challenges for healthcare systems. One of the key global social trends is the aging of the population (Wolf et al., 2021), characterized by an increase in the number of elderly individuals. It is projected that the proportion of older people (aged 65 and older) in the overall EU population will increase from 21.1% (94.3 million) at the beginning of 2022 to 32.5% (136.1 million) in 2100. Around 2050, the number of people aged 65 and older will make up 25% of the population, surpassing the number of those under 25 (United Nations, 2019). With the decline in the overall EU population by 2100, this is the only age group with the potential to grow (both in relative and absolute terms), confirming the ongoing process of population aging (Eurostat, 2023).

Ongoing demographic changes have a significant impact on the economy and its various segments (Halicka, 2024). It is necessary to adapt infrastructure, services, healthcare, and social care to accommodate the shifting age structure of the population. The aging population will increase the demand for elderly care. Healthcare systems will need to adjust to this trend by offering high-quality geriatric care and long-term senior care. Social security systems, especially those based on a pay-as-you-go model, where pensions are paid from the current contributions of working individuals (as in Poland), may face destabilization. The rise in healthcare costs will also be driven by the need to address chronic and lifestyle-related diseases and the growing demand for preventive diagnostic tests.

Global pandemics like COVID-19 pose a significant challenge to modern healthcare and medicine. Significant changes are typical for human behaviour as well (Florek & Lewicki, 2022; Mishchuk et al., 2023). They underscore the need for rapid responses and increased capacity to control infectious diseases. Finally, rapid technological advancement and the increasing volume of medical data require the adaptation of medical practices, as well as the implementation of new regulations and procedures to ensure the security and privacy of data.

These challenges shape innovative processes and the way healthcare is delivered. To ensure better quality of care and health outcomes for patients, modern medicine focuses on leveraging advanced technologies, personalizing healthcare, and improving access to medical services.

One of the tools introducing revolutionary innovations in healthcare is artificial intelligence (AI) (Alberich-Bayarri, Pastor, González, & Castro, 2019; Doanh et al., 2023). It can offer convenient access to medical care, diagnostics, and monitoring outside of hospital settings (Lee & Yoon, 2021).

The literature review conducted for the purpose of this article has allowed for the identification of the main areas of AI applications in medicine and the research topics within them. The identified main research topics, along with sample publications and the research objectives described in these articles, are presented in Table 1.

Table 1. The area of AI applications in medicine [Source: Own study]

The area of AI applications in medicine	The role of AI	Publication	The research problem, objectives
Medical diagnosis	Recognition of diseases and interpretation of medical test results such as X-ray images, computer tomography (CT), and magnetic resonance imaging (MRI)	Parasher, Wong, & Rawat, 2020	A discussion on the role of AI in gastrointestinal endoscopy and future development opportunities
		Gulshan et. al., 2016	Applying deep learning to create an algorithm for automated detection of diabetic retinopathy and diabetic macular edema in retinal fundus photographs
		Hwang et. al., 2019	Developing a deep learning–based algorithm that can classify normal and abnormal results from chest radiographs with major thoracic diseases including pulmonary malignant neoplasm, active tuberculosis, pneumonia, and pneumothorax and validating the algorithm's performance using independent data sets
Prediction and risk assessment	Patient data analysis and assistance in predicting treatment outcomes and assessing disease risk, enabling better clinical decision-making	Navarro et. al., 2021	Assessing the methodological quality of studies on prediction models developed using machine learning techniques across all medical specialties
		Kanegae et. al., 2020	Using machine learning techniques to develop and validate a new risk prediction model for new-onset hypertension
		de Hond et. al., 2022	Identification of actionable guidance for those closely involved in AI-based prediction model (AIPM) development, evaluation and implementation including software engineers, data scientists, and healthcare professionals and to identify potential gaps in this guidance
Prediction of epidemics	Analysis of epidemiological data and assistance in predicting potential outbreaks of infectious diseases, which is crucial for public health	Kolozsvári et. al., 2021	Using the official epidemiological data to forecast the epidemic curves (daily new cases) of the COVID-19 using Artificial Intelligence (AI)-based Recurrent Neural Networks (RNNs), then comparing and validating the predicted models with the observed data
		Gruenwald, Jain, & Groppe, 2021	Detailed technical description of the role Artificial Intelligence plays in various stages of a disease outbreak, using COVID-19 as a case study
		MacIntyre et. al., 2023	The role of AI in epidemic surveillance and summary of several current epidemic intelligence systems including ProMED-mail, HealthMap, Epidemic Intelligence from Open Sources, BlueDot, Metabiota, the Global Biosurveillance Portal, Epitweetr and EPIWATCH
Personalized medicine	Providing a personalized approach to treatment, tailored to individual patient needs based on genetic analysis and other data	Schork, 2019	Analysis of contributions of AI in advancing personalized medicine, pointing out the limitations of many AI techniques in developing personalized medicines, presenting areas for further research
		Awwalu, Garba, Ghazvini, & Atuah, 2015	An overview of the application and ability of artificial neural network (ANN), support vector machines (SVM), Naïve Bayes, and fuzzy logic in solving personalized medicine problems
		Gifari, Samodro, & Kurniawan, 2021	Review of selected applications of AI tools in the development of personalized medicine in the context of their performance, interpretability and clinical relevance
Surgical suport	Robotics and AI systems can assist surgeons during procedures, enabling precise surgeries and reducing recovery time	Hashimoto, Rosman, Rus, & Meireles, 2018	Summary of major topics related to artificial intelligence (AI), including their applications and limitations in surgery. Discussion of key capabilities of AI to help surgeons understand and critically evaluate new AI applications and contribute to new developments
		Hashimoto, Rosman, Meireles, 2021	A history, principles, and main subfields of artificial intelligence (AI), examples of current and near-future use cases for AI in surgery, followed by a discussion of the ethical implications of AI and its potential impact on health policy
		Zhou, Guo, Shen, & Yang, 2020	Review of the recent successful and influential applications of AI in surgery from preoperative planning and intraoperative guidance to its integration into surgical robots, summary of the current state, emerging

			trends, and major challenges in the future development of AI in surgery
Patient monitoring	AI can assist in real-time patient monitoring by analyzing data from medical equipment and wearable devices, enabling a quick response to changes in the patient's health	Shaik et. al., 2023	A comprehensive review of Remote Patient Monitoring (RPM) systems, including advanced technologies employed, the impact of AI on RPM, challenges, and trends in AI-enabled RPM. The analysis covers the benefits and challenges of patient-centric RPM architectures facilitated by IoT devices and sensors using cloud, fog, edge, and blockchain technologies
		Baig, GholamHosseini, Moqeem, Mirza, & Lindén, 2017	Investigating barriers and challenges of wearable patient monitoring (WPM) solutions adopted by clinicians in acute, as well as in community, care settings.
		Malche et. al., 2022	A proposal for an Intelligent Remote Patient Activity Tracking System that can monitor patient activities and vital signs during these activities based on attached sensors
Medical Data Management	AI assists in the analysis of vast amounts of medical data, contributing to the improvement of medical data management, predicting trends, and identifying patterns	Wehbe, Al Zaabi, & Svetinovic, 2018	A proposal for a coupled AI-Blockchain EHR management system. The goal is to provide a platform that leverages blockchain and artificial intelligence (AI) for secure EHR management, efficient data integration, and reliable computer-aided diagnoses
		Mehta, Pandit, & Shukla, 2019	Systematic mapping study to identify and analyze research on big data analytics and artificial intelligence in healthcare, in which 2421 articles between 2013 and February 2019 were evaluated. The results of this study will help understand the needs in application of these technologies in healthcare by identifying the areas that require additional research
		Hariri, Fredericks, & Bowers, 2019	Presentation on Artificial Intelligence Techniques Applied to Large Data Sets. This article reviews previous work in big data analytics and presents a discussion of open challenges and future directions for recognizing and mitigating uncertainty in this domain
Pharmacology	AI helps accelerate the drug discovery process, identify potential therapeutic targets, and design new drugs	Zhavoronkov, Vanhaelen, & Oprea, 2020	Discuss on current trends in the use of AI/ML in health care and the impact of AI/ML context of the daily practice of clinical pharmacologists
		Al Meslamani, 2023	The discussion of the potential of artificial intelligence in revolutionizing pharmacy practice is a promising exploration. It involves an examination of the current state of AI applications in pharmacy, identifying gaps and challenges, and suggesting potential strategies for integrating AI tools into daily practice. This integration has the potential to propel the pharmaceutical sector into a new era of healthcare, characterized by increased personalization and efficiency
		Rubinic et. al., 2023	Exploring the possibility of employing large language models (LLMs) – a type of artificial intelligence (AI) – in clinical pharmacology, with a focus on its possible misuse in bioweapon development
Healthcare and Healthcare Company Management	AI systems can support healthcare organizations in optimizing processes, detecting abuses, and reducing care costs	Dicuonzo, Donofrio, Fusco, & Shini, 2023	Investigating how AI supports the effective and efficient management of the healthcare system by examining the Humber River Hospital in Toronto using the case study methodology
		Kulkov, 2021	Identifying exactly how AI affects the key and supporting business processes of pharmaceutical companies
		Cubric, 2020	Review of AI implementations in various business sectors (including healthcare)

The field of medical diagnostics is particularly sensitive to the emergence of issues resulting from the global trends of an aging society. There is an increasing demand for complex medical examinations and the monitoring of chronic diseases. The growing number of patients leads to challenges in accessing healthcare services, longer waiting times for medical appointments, and delays in diagnosis. A shortage of specialists, including radiologists and technicians, also hinders access to medical tests. Elderly patients often require more advanced examinations due to their multiple health conditions, which increases healthcare costs. Complex monitoring of chronic diseases, privacy issues, and physical barriers in accessing medical facilities are further challenges in the context of an aging society.

With age, the risk of various health conditions such as heart disease, cancer, and neurodegenerative disorders increases, leading to changes in diagnostic needs. Diagnostic systems must adapt to these specific requirements, which may call for innovative technologies and more advanced tests. All of these factors create challenges that medical diagnostic systems need to address to ensure effective care for elderly patients. It appears that modern technologies, including AI, have the potential to contribute to the improvement of healthcare and serve as effective tools for contemporary and future medicine to meet the challenges posed by current developmental trends. They have the potential to save time and money while promoting patient engagement in using technologically supported systems offered by healthcare institutions (Lee & Yoon, 2021).

Artificial intelligence (AI) has already demonstrated significant potential in the field of medical diagnostics. Deep learning algorithms, especially convolutional neural networks, have become a popular choice for analyzing medical images (Litjens et al., 2017; Shen, Wu, & Suk, 2017). These machine learning algorithms have been applied in various tasks related to medical images, including image classification, object detection, segmentation, and registration (Litjens et al., 2017).

AI tools can be utilized throughout the entire radiological process, starting from image quality in acquisition, automated image classification, quantitative image analysis, up to reporting and management. They achieve results similar to human capabilities and should be viewed as a supplementary rather than a replacement for radiologists (Alberich-Bayarri et al., 2019). These tools can expedite the diagnostic process, enhance diagnostic quality, facilitate early disease detection, and contribute to improving diagnostic service accessibility (Rigby, 2019; Lee & Lee, 2020; Saleh et al., 2022; Morgan et al., 2021; Dreyer & Allen, 2018).

The use of AI in the analysis of medical images has been explored in various fields, including neurology (Giannos, 2023); retinal studies (Saleh et al., 2022), pulmonology (Yanagawa et al., 2021), digital pathology (Bizzego et al., 2019); breast imaging (Erickson, Korfiatis, Akkus, & Kline, 2017; Sidey-Gibbons & Sidey-Gibbons, 2019; Zhou et al. 2021), cardiology (Sengupta & Chandrashekhar, 2021), abdominal imaging (Park, Cho, & Kim, 2023), musculoskeletal imaging (Litjens et al., 2017), dermatology (Esteva et al., 2017), ophthalmology (Afifi-Sabet, 2018); gynecology (Sone et al., 2021), surgery (Lewicki et al., 2021). AI has the potential to enhance diagnostic accuracy, improve efficiency, and support healthcare professionals in decision-making processes (Harada, Katsukura, Kawamura, & Shimizu, 2021; Erickson et al., 2017, Jiang et al., 2017). The most common diagnostic applications of AI are in oncology, neurology, and cardiology (Jiang et al., 2017). Currently, diseases in these areas are major causes of death, making early diagnosis crucial to prevent the deterioration of patients' health.

Support for diagnosticians can also involve providing the most up-to-date medical knowledge from various sources (journals, textbooks, clinical practice) (Sitthipon et al., 2022). AI has a high potential for analyzing large and complex datasets to create predictive models that personalize and improve diagnosis, prognosis, monitoring, and therapy administration for the enhancement of individual health outcomes. The predictive models developed are useful in assessing health risk and support clinical decision-making (Collins & Moons, 2019). Summarizing, AI, especially deep learning algorithms, has shown promise in the field of medical diagnostics. Nevertheless, there are still challenges and directions for future research in this field.

One of the solutions needed is how to effectively utilize the vast amount of available healthcare data in computer systems, which raises questions about data security and patient privacy. It turns out that the assessment of data quality and data curation (including medical images) in the context of AI and DL can take up to 80% of data specialists' time. This can make proper implementation challenging and may even lead to incorrect data processing or erroneous conclusions (van Ooijen, 2019).

The need for AI in diagnostics is also linked to the high number of errors made in human diagnoses. Taylor (2019) stated that 60% of all medical errors and an estimated 40,000-80,000 deaths annually in U.S. hospitals are due to diagnostic errors. AI systems can help reduce diagnostic and therapeutic errors (Lee & Yoon, 2021; Uzialko, 2019).

The broader applications of artificial intelligence offer numerous possibilities, but on the other hand, they can raise societal concerns (Ikkatai, Hartwig, Takanashi, Yokoyama, 2022; Kieslich, Lünich, & Došenović, 2023; Wach et al., 2023). The dark side of). These concerns stem from the need to ensure the safety of patient data and privacy (Murdoch, 2021), uncertainties regarding outcomes (arising from machine learning), and the high costs of implementing AI-based solutions for medical institutions (Ahmad, Rahim, Zubair, & Abdul-Ghafar, 2021).

Concerns related to the use of artificial intelligence in medical diagnosis extend to both doctors and diagnostic experts, as well as patients who traditionally relied solely on human knowledge - specialist doctors. Raising public awareness about the increasing use of AI in medicine, its advantages, and disadvantages will contribute to more informed decision-making and greater openness to these solutions in the future. Many researchers emphasize the need for ongoing education for both doctors, diagnostic experts, and patients (Lee & Yoon, 2021).

The aim of the conducted research was to assess the attitude of the Polish society towards the use of artificial intelligence for medical diagnostics.

The remaining part of the article has the following structure. In the next section, the results of the literature review in the context of the relationships between the three studied constructs were presented, allowing for the formulation of research hypotheses and a theoretical model. Next, in the section Research methodology, the research process was described, along with the methods and research tools employed. Additionally, the research sample was characterized, taking into account its demographic features. Subsequently, the results of the research were presented, allowing for the statistical verification of the research hypotheses. The authors' research findings were discussed in the context of previous research results by other authors. In the Conclusions section, the main methodological and practical conclusions were presented, limitations of the research were indicated, and future research directions were suggested.

LITERATURE REVIEW AND THEORETICAL MODEL

Acceptance and understanding of AI by patients are essential for the implementation of artificial intelligence in medical diagnostics. Society's attitude towards the application of artificial intelligence (AI) in medical diagnostics is dependent, among other factors, on the level of trust in AI systems, the public's awareness of the benefits and risks associated with AI in medicine, and the ability to handle technology.

Patients generally exhibit a positive attitude towards using artificial intelligence-based systems for health purposes (Esmaeilzadeh, Mirzaei, & Dharanikota, 2021). In their opinion, diagnoses made by AI are perceived to be more accurate than those made by doctors (Stai et al., 2020). They view clinical applications of AI as beneficial to their healthcare needs and believe that AI can help them understand diagnosis outcomes (Richardson et al., 2021). Patients recognize the benefits in terms of improving the quality of medical diagnostics (Ayad et al., 2023) and reducing human errors.

However, they express concerns regarding safety, privacy, and the potential increase in healthcare costs associated with the use of medical diagnoses based on artificial intelligence (Chernobrivtseva & Misyurin, 2022). Some of them are skeptical about AI's ability to accurately assess their health (Gaczek, Pozharliev, Leszczyński, & Zieliński, 2023).

The lack of trust stems from the fear of machine errors and the need for human knowledge in decision-making (Poon & Sung, 2021; Boiko et al., 2021) and the lack of AI regulation (Kerasidou, Kerasidou, Buscher, & Wilkinson, 2022).

Identifying and addressing these concerns (Hanhui, 2019) is crucial for the acceptance of AI by its users (medical staff and patients) (Zhang et al., 2020). Previous studies on medical personnel suggest that not everyone is willing to accept the use of medical AI devices (Laï, Brian, & Mamzer, 2020; Turja, Aaltonen, Taipale, & Oksanen, 2020). Patient attitudes towards AI are not well understood (Young, Amara, Bhattacharya, & Wei, 2021). There is still limited knowledge about the readiness of the general population to undergo medical procedures involving artificial intelligence. Few studies have focused on assessing consumer perspectives on the use of AI in medicine, including understanding the process of building patient trust in medical AI applications. Recent research has emphasized the importance of system explainability in increasing user trust and reliance on medical artificial intelligence in diagnostic support (Rong, Castner, Bozkir, & Kasneci, 2022). Gips and Bahramisharif (2022) highlight that trust in AI applications can increase by demonstrating that AI technologies can improve clinical outcomes and engaging clinicians in the decision-making process.

The successful implementation of artificial intelligence-based systems requires a thorough examination of users' attitudes and perceptions towards artificial intelligence (Romero-Brufau et al., 2020; Bilan et al., 2023). It necessitates a profound understanding of the factors influencing the acceptance of AI-based services by potential users. As noted by Czemiel-Grzybowska (2022), any kind of innovation implementation process depends on openness to new technology and solutions (Czemiel-Grzybowska, 2022). Many authors emphasize the urgent and continuous need for research on the societal and ethical aspects of AI technology applications (Robinson, 2020).

In shaping trust in the application of artificial intelligence in medical diagnostics, openness to new technologies plays a crucial role. Both doctors and patients hesitate to fully trust and adopt AI-based technologies in medicine due to the "black box" effect, where the internal workings of algorithms are not fully understandable (Nolan, 2023). There is still a need to improve trust in AI models (Sushma, Goud, Nikhil, & Reddy, 2021). The adoption and usage of artificial intelligence systems may be contingent upon the trustworthiness and acceptance levels attributed to these tools (Sohn, Kwon, 2020). Also, Pishnyak and Khalina (2021), when studying the determinants shaping innovation openness, considered trust as one of the elements. Considering the importance of openness to new technologies and its role in building trust in technology, the following hypothesis has been formulated:

H1: Openness to new technologies statistically significantly influences a higher level of trust in the application of AI in medical diagnostics.

Trust in artificial intelligence in medical diagnostics is the subject of research (Juravle, Boudouraki, Terziyska, & Rezlescu, 2020), especially from the perspective of medical staff (Tucci, Saary, & Doyle, 2022; Asan, Bayrak, & Choudhury, 2020). The willingness to trust the application of artificial intelligence in medical diagnostics refers to the inclination or readiness of individuals (both medical staff and patients) to trust and rely on artificial intelligence technologies for diagnostic purposes. It encompasses the psychological and attitudinal aspects of using artificial intelligence as a valuable tool in medical diagnostics. It plays a crucial role in the successful integration and acceptance of AI technologies in healthcare. A high level of willingness indicates an open approach to AI-based medical diagnostics, while lower willingness follows from concerns about this form of diagnostics. Determinants of readiness to implement artificial intelligence in medical diagnostics include (Hsieh, 2023; Tran et al., 2021): perceived effectiveness of artificial intelligence in terms of diagnostic accuracy, level of trust in artificial intelligence systems, ethical considerations, and understanding of potential benefits and risks associated with the implementation of artificial intelligence in medical diagnostics.

Areas such as reliance on AI, trust in it, and willingness to use it have not been fully explored within the patient population. Knowledge in this regard is crucial because implementing solutions based on artificial intelligence without considering the beliefs of potential users (medical staff, as well as patients) and their readiness to accept AI-based devices can lead to the waste of resources. This is especially important in healthcare, as patient engagement is a significant determinant of healthcare quality. If patients do not perceive the use of medical AI devices as beneficial, they may have a negative view of the entire process of receiving medical services using AI. Therefore, the following hypothesis has been formulated:

H2: Willingness to trust the application of AI in medical diagnostics determines the perceived impact of AI application on the quality of medical diagnostic services improvement.

Research on technology acceptance confirms that demographic characteristics (age, gender, and education) determine attitudes towards technology. Older adults, men, and individuals with higher education generally tend to have more positive attitudes towards technology (Lee et al., 2019).

According to some researchers (Lee, 2010), the influence of demographic factors on the acceptance of information technology is diminishing; respondents exhibit a positive attitude towards the benefits of technology and its adoption regardless of gender, age, education, and income levels.

The following hypotheses were formulated to investigate the relationship between attitudes towards the application of AI in medical diagnostics and socio-demographic characteristics:

H3.1. The age determines the openness to new technologies (OP)

H3.2. The gender determines the openness to new technologies (OP)

H3.3. The education level determines the openness to new technologies (OP)
H4.1. The age determines the willingness to trust AI in medical diagnostics (T)
H4.2. The gender determines the willingness to trust AI in medical diagnostics (T)
H4.3. The education level determines the willingness to trust AI in medical diagnostics (T)
H5.1. The age determines the perceived impact of AI application on the quality of medical diagnostic services improvement (PI)
H5.2. The gender determines the perceived impact of AI application on the quality of medical diagnostic services improvement (PI)
H5.3. The education level determines the perceived impact of AI application on the quality of medical diagnostic services improvement (PI)

RESEARCH METHODOLOGY

Research sample

The survey was conducted in June 2023, on a representative sample of 1063 Polish adults. A random sample selection method was employed. For data collection, the CATI (Computer-Assisted Telephone Interviewing) technique was used. The obtained sample size (1063), with an assumed margin of error of 3% and a confidence level of 95% ensured the sample's representativeness.

The structure of respondents varied based on demographic characteristics: gender, age, and education. The sample size and its demographic structure are presented in Table 2.

Table 2. Respondents' demographic structure based on gender, age, and education [Source: Own study]

	Frequency	Percentage
Gender		
Female	554	52.1
Male	508	47.8
Other	1	0.1
Age		
18-25 years old	148	13.9
26-40 years old	319	30.0
41-60 years old	366	34.4
over 60 years old	230	21.6
Education level		
Primary or lower secondary education	28	2,6
Basic vocational education	115	10,8
Secondary (high school/ post-secondary	468	44,0
Higher education (University level)	452	42,5
Declined health status		
Very good	92	8,7
Good	476	44,8
Average	363	34,1
Rather poor	83	7,8
Poor	36	3,4
Hard to say	13	1,2

Research measurements

Considering that the studied constructs are not directly measurable and represent unobservable constructs, one of the research objectives was to develop measurement scales for the three measurement constructs: openness to new technologies (OP), willingness to trust AI in medical diagnostics (T), and perceived impact of AI application on the quality of medical diagnostic services improvement (PI). The proposed measurement variables within the constructs OP and T were assessed by respondents using a 5-point Likert scale, where: 1 - indicated "strongly disagree," and 5 - indicated "strongly agree." In the case of assessing the impact of AI on the quality of medical services, a 5-point Likert scale was also used, where: 1 – indicated significant deterioration, 5 indicated significant improvement.

Subsequently, the obtained results were subjected to confirmatory factor analysis (CFA) to verify the proposed measurement scales. Variable reduction was conducted taking into account regression coefficient value and absolute values of the covariances for standardized residuals. From the initial set of observable variables, variables were excluded if their regression coefficient value was below 0.6, and if the absolute values of the standardized residual covariances exceeded 2 (as shown in Table 3).

The reliability of the adopted measurement scales was assessed using two measures: Cronbach's alpha coefficient (α-Cronbach) and Composite Reliability (CR). For both measures, an acceptable level should exceed 0.7. Validity was evaluated in terms of convergent validity using the Average Variance Extracted (AVE). The AVE value should exceed 0.5. A Cronbach's alpha value above 0.7 confirms high reliability of the scales and their suitability for measuring the studied constructs. The Cronbach's alpha coefficients for the constructs are as follows: OP = 0.765, T = 0.847, PF = 0.854 (Table 4).

Table 3. Standardized regression weights before and after CFA [Source: Own study]

Constructs and items	Standardized regression weights before and after CFA		Variable symbol
	Before	After	
Openness to new technologies (OP)			
I enjoy using new technologies	0.780		Removed
When I hear about new technology, I look for ways and opportunities to try it out	0.797		Removed
Among my peers/friends/family, I am usually the first person to try new technologies	0.692		Removed
I enjoy experimenting with new technologies	0.786	0.549	OP1
Thanks to science and technology, the world is a better place	0.686		Removed
Science and technology make our lives easier and more comfortable	0.799	0.857	OP2
Science and technology create more opportunities for the development of society	0.751	0.831	OP3
Willingness to trust AI in medical diagnostics (T)			
The development of artificial intelligence is essential for the advancement of our economy	0.734		Removed
The use of AI in medicine may raise moral dilemmas and doubts about entrusting the health and life of a human to artificial intelligence (reverse scale)	0.248		Removed
I would be willing to trust AI for diagnosis or treatment	0.741		Removed

When undergoing examinations, I would prefer artificial intelligence (AI) to be used in imaging studies (e.g., ultrasound, computer tomography, magnetic resonance, X-ray)	0.851	0.867	T1
I would feel comfortable if my doctor used AI-based tools for diagnosing diseases and selecting treatment methods	0.794	0.797	T2
Artificial intelligence (AI) could diagnose various conditions more accurately than humans	0.749	0.781	T3
Perceived impact of AI application on the quality of medical diagnostic services improvement (PI)			
The application of AI in medical diagnostics will improve the quality of services in the areas of:			
Quality of diagnoses (accuracy)	0.847	0.867	PF1
Number of medical errors	0.753	0.744	PF2
Patient-physician relationships	0.679		Removed
Security of patients' private medical data	0.648		Removed
Accuracy and validity of selected treatment methods	0.844	0.841	PF3
Speed of diagnosis and treatment	0.793		Removed
Access to healthcare services	0.690		Removed

* Variable removed due to regression coefficient value was less than 0.6 and if the absolute values of the covariances for standardized residuals were greater than 2.

Table 4. Descriptive statistics, Cronbach's α, Average Variance Extracted and Composite Reliability for all constructs [Source: Own study]

Constructs and items	Mean (M)	Factor Loading	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
Openness to new technologies (OP)					
OP1. I enjoy experimenting with new technologies	3.33	0.549			
OP2. Science and technology make our lives easier and more comfortable	3.89	0.857	0.765	0.797	0.575
OP3. Science and technology create more opportunities for the development of society	3.91	0.831			
Willingness to trust AI in medical diagnostics (T)					
T1. When undergoing examinations, I would prefer artificial intelligence (AI) to be used in imaging studies (e.g., ultrasound, computer tomography, magnetic resonance, X-ray)	3.65	0.867			
T2. I would feel comfortable if my doctor used AI-based tools for diagnosing diseases and selecting treatment methods	3.42	0.797	0.847	0.856	0.666
T.3 Artificial intelligence (AI) could diagnose various conditions more accurately than humans	3.63	0.781			
Perceived impact of AI application on the quality of medical diagnostic services improvement (PI)					
PF1. Quality of diagnoses (accuracy)	3.51	0.867			
PF.2 Less number of medical errors	3.28	0.744	0.854	0.859	0.671
PF3. Accuracy and validity of selected treatment methods	3.52	0.841			

RESEARCH RESULTS

At the beginning of the survey, respondents were asked if they had ever heard of artificial intelligence (AI). A significant majority of respondents, as many as 96.0% (1020 individuals), answered that they had heard of AI, while only 4.0% (4 individuals) provided a negative response. In response to the question: Have you heard about the use of solutions employing artificial intelligence in the medical sector? fewer people answered affirmatively, with 60.6% (644 individuals) responding positively. The remaining 39.4% (419 individuals) provided a negative response.

However, since a significant portion of the respondents had not heard about the potential use of AI in medical services, a brief explanation of potential areas of AI application in medical diagnostics was provided at the beginning of the survey questionnaire: *The use of artificial intelligence methods in medical diagnostics involves the application of AI techniques (neural networks, genetic algorithms, expert systems) in the automated analysis of medical images to assist in medical diagnostics of pathological tissue conditions (such as tumors and inflammations). Artificial intelligence can analyze medical images, including computer tomography (CT), magnetic resonance imaging (MRI), ultrasound (USG), or X-rays, to detect pathological changes. Through machine learning, algorithms can recognize anatomical structures and identify signs of diseases, such as tumors and other conditions (e.g., psoriasis, acne). Artificial intelligence can also analyze the results of laboratory tests, such as blood morphology or biochemical tests, to detect abnormalities and provide accurate diagnoses. Algorithms can help identify patterns that indicate specific diseases and predict the risk of complications.*

To evaluate the research hypotheses Structural Equation Modelling (SEM) was utilized, enabling the examination of causal connections among variables. AMOS software was used for Structural Equation Modeling. Generalized least squares (GLS) approach to estimating fit and coefficients was adopted. The validation of the two hypotheses was carried out using the structural path coefficients. Figure 1 illustrates the estimated structural paths between constructs and variables.

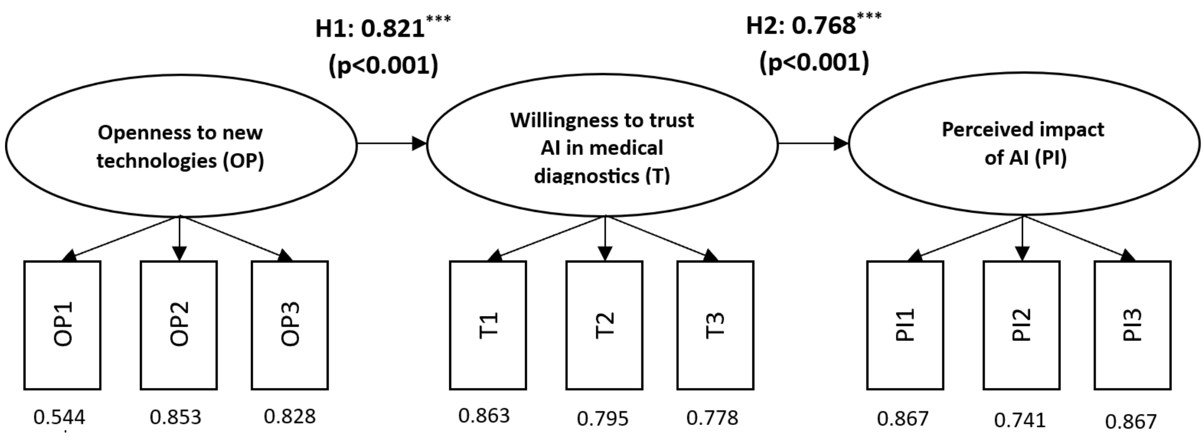

Figure 2. Measurement model [Source: Own study]

The examination of factor loadings on pathways and the p-value demonstrates the confirmation of two hypotheses (as shown in Table 5).

Table 5. The results of hypothesis statistical verification [Source: Own study]

Relationship between Constructs	Estimate	Standard Error	Capability Ratio	*p*	Hypothesis Testing
H1: OP→T	0.821	0.049	16.872	***	Support
H2: T→PI	O.678	0.029	23.507	***	Support

$\chi 2$ = 74,40; degrees of freedom (df) = 25; $\chi 2$/df = 2,976; p < 0.001; RMSEA = 0.043; GFI = 0.984; CFI=0.945L AGFI=0.972; *** the adopted level of statistical significance was 0.001

Table 6 displays the selected indices used to evaluate the goodness of fit for the SEM model, along with the target values for each. The model fit indices acquired validate that the model fits appropriately.

Table 6. SEM fit indices [Source: based on literature review]

Model fit indices	Level of acceptance	Sources
Chi-square/Degrees of freedom ($\chi 2$/df)	desire < 3, acceptable < 5	Hu, Bentler, 1999;
Comparative fit index (CFI)	0.9 acceptable 0.95 desire	Hwang, Kim, 2007; Choudhury, Karahanna,
Root mean square error of approximation (RMSEA)	0.05 (0.08)	2008; Iacobucci, 2010;
GFI - The goodness-of-fit index	>0.9	Konarski, 2023; Kline
AGFI - The adjusted goodness-of-fit index	>0.9	2015;

One of the research objectives was to determine to what extent the demographic characteristics of respondents influence their:

- openness to new technologies (OP);
- willingness to trust AI in medical diagnostics (T);
- perceived impact of AI application on the quality of medical diagnostic services improvement (PI).

The following research hypotheses were subjected to statistical verification:

H3.1. The age determines the openness to new technologies (OP)
H3.2. The gender determines the openness to new technologies (OP)
H3.3. The education level determines the openness to new technologies (OP)
H4.1. The age determines the willingness to trust AI in medical diagnostics (T)
H4.2. The gender determines the willingness to trust AI in medical diagnostics (T)
H4.3. The education level determines the willingness to trust AI in medical diagnostics (T)
H5.1. The age determines the perceived impact of AI application on the quality of medical diagnostic services improvement (PI)
H5.2. The gender determines the perceived impact of AI application on the quality of medical diagnostic services improvement (PI)
H5.3. The education level determines the perceived impact of AI application on the quality of medical diagnostic services improvement (PI)

For the statistical verification of hypotheses H3.2, H4.2, and H5.2, a non-parametric Mann-Whitney test was applied. To verify the remaining hypotheses, a non-parametric Kruskal-Wallis test was used (Table 7).

Table 7. Kruskal-Wallis test results [Source: Own study]

Hypotheses		Z value	p-value	Hypothesis testing
H3.2.	OP→Gender	-2,397	0.017	Support
H4.2.	T→Gender	-2,757	0.006	Support
H5.2.	PI→Gender	-2,793	0.005	Support

The obtained results confirmed that there are statistically significant differences in the assessment of these constructs between men and women. The average rank values affirmed that men are more open to new technologies than women, men exhibit a higher willingness to trust the application of AI in medical diagnostics, and men rate the potential impact of AI in medical diagnostics on the improvement of healthcare services more highly.

Table 8. Mann-Whitney test results [Source: Own study]

Hypotheses		p-value	Hypothesis testing
H3.1.	OP→Age	0.214 (p>0.05)	Reject
H4.1.	T→Age	0.001 (p<0.05)	Support
H5.1.	PI→Age	0.020 (p<0.05)	Support
H3.3.	OP→Education	0.001 (p<0.05)	Support
H4.4.	T→ Education	0.001 (p<0.05)	Support
H5.4.	PI→ Education	0.079 (p>0.05)	Reject

The age of respondents does not have a statistically significant impact on openness to new technologies (H.3.1 was rejected; p=0.214). The age of respondents, however, determines willingness to trust AI in medical diagnostics (T) and the perceived impact of AI application on the quality of medical diagnostic services improvement (PI).

Pairwise comparisons of age groups revealed statistically significant differences in the level of trust propensity between respondents representing the groups: 18-25 years old and 41-60 years old; between 18-25 years old and over 60 years old; between 26-40 years old and 41-60 years old, between 26-40 years old and over 60 years old. However, there is no statistically significant difference in the assessment of construct T between respondents 18-25 years old and 26-40 years old as well between 41-60 years old over 60 years old. The average rank values confirm that, generally, older people exhibit a higher level of willingness to trust AI in medical diagnostics (T).

Pairwise comparisons of age groups revealed statistically significant differences in the level of perceived impact of AI application on the quality of medical diagnostic services improvement (PI) between respondents representing the groups: between 26-40 years old and over 60 years old; between 18-25 years old and over 60 years old. The average rank values confirm that, generally, older people exhibit a higher level of perceived impact of AI application on the quality of medical diagnostic (PI).

The level of education of respondents determines their openness to new technologies (OP) and propensity for trust (T). Pairwise comparisons of respondents belonging to different educational level groups revealed that willingness to trust AI in medical diagnostics (T) is closely correlated with the level of education. There are statistically significant differences in the assessment of Constructs OP and T between respondents with primary, vocational, and secondary education and respondents with higher education. The latter group exhibits a higher level of willingness to trust AI in medical diagnostics (T) and higher level of openness to new technologies (OP).

The perceived impact of AI application on the quality of medical diagnostic services improvement (PI) is not statistically different within the education groups.

DISCUSSION

The obtained results are consistent with findings from other authors working on the issue of awareness and perception of AI application in medical diagnostics (Ibba, et al., 2023). Generally, respondents indicated a positive attitude (trust) towards the use of AI in medical diagnostics. The average results of variable measurements confirm the positive outlook of the respondents (71 – 3.65, T2 – 3.42, T3 – 3.63). Similar results were obtained by the team of Ibba, et al. according to which 74% of respondents would feel comfortable if their doctor used AI (Ibba, et al., 2023).

Results regarding the impact of the demographic variable, such as age, on the perceived trust in the use of AI in medical diagnosis, have shown that older people exhibit a higher level of willingness to trust AI in medical diagnostics (T). These results are in contradiction with the findings obtained by Ibb et al., who demonstrated that with age, there is a decrease in positive attitudes towards AI applications (Ibba, et al., 2023). The observed relationship between the level of education and the perceived tendency to trust AI in medicine was also confirmed in studies conducted by Ibba, et al. (2023).

Results related to the perceived trust in AI by both genders of respondents were not confirmed by other researchers. The conducted studies confirmed that men are more inclined to trust AI applications than women. Also, studies conducted by Bahakeem et al. (2023) confirmed that men exhibit a higher level of positive attitude towards AI. For the opposing view, in the studies conducted by Ibba et al., such a relationship was not confirmed. A statistically significant correlation between trust and the level of education among respondents has also been confirmed by other researchers such us Ongen et al. (2020)

The perceived impact of AI application in medical diagnostics was examined by respondents in the context of improving the accuracy of diagnoses, reducing errors, and enhancing the precision and validity of selected treatment methods. Respondents indicate that the application of AI will have a modest but still positive impact on the analyzed indicators of improving the quality of diagnostic services. Research conducted by Ongen et al. (2020) also confirmed that the surveyed individuals believe that AI can be more efficient and effective in providing accurate diagnoses. The examined relationships between the gender of respondents and the perceived impact on the quality of diagnostics confirmed statistically significant dependencies, which was not consistent with the results of Ongena et. al., 2020. The obtained results from the sample of Polish respondents diverge significantly from the findings of other authors regarding the relationship between the age of respondents and the perceived impact of AI on improving the quality of diagnostics. Polish respondents are more optimistic with age. Generally, older people exhibit a higher level of perceived impact of AI application on the quality of medical diagnostic. According to the results obtained by Ongena et. al., (2020) indicators related to the efficiency of AI application in diagnostics were weakly negatively correlated with the age of respondents.

CONCLUSIONS

Building societal trust in the use of AI in medical diagnostics and the ability to use technology effectively in the long run will contribute to the broader adoption of solutions that can be used in everyday life, even without the need for a doctor's visit.

The authors' focus was particularly on examining the relationships among three variables: openness to new technologies in general, trust in AI in medical diagnostics, and the perceived impact of AI applications on the improvement of the quality of medical services, along with demographic variables (age, gender, and education level).

The gender of respondents is among the demographic variables that differentiate the opinions of respondents regarding three analyzed constructs: openness, trust, and perceived impact of AI application on the quality of diagnostic services. Men exhibit a higher level of openness to new technologies, thus a higher level of trust in AI applications and a higher perception of the positive impact of AI on the quality of diagnostic services. Although other researchers often do not confirm statistically significant dependencies of this kind in Polish conditions, it seems to be a cultural factor, also associated with more traditional roles attributed to each gender, particularly in rural contexts.

The level of education also has a decisive impact on the perceived trust of respondents in the applications of AI in diagnostics and the perception of the positive impact of AI applications on the quality of medical diagnostic services, which confirms the need for ongoing educational initiatives.

The surprising results concerning the Polish society are associated with the demonstrated statistically significant relationship between two variables: trust in AI and the perceived impact on improving diagnostic services and the age of respondents. Contrary to expectations, older respondents exhibit a higher level of trust in AI and a higher perception of the positive impact of AI on the quality of medical services. On one hand, the observed relationships may stem from a better familiarity with diagnostic services and the frequency of their utilization, as well as a perceived need for improvements in terms of diagnostic quality, fewer errors, etc. Undoubtedly, this could be an interesting direction for further research.

In countries facing a significant shortage of medical professionals, there will be a strong temptation to increase the intensity of utilizing AI-based solutions. The development of technology applications will also necessitate the enhancement of skills among physicians collaborating with AI technology. Research focused on assessing the dynamics of developmental processes, including physicians' skills, problem-solving abilities, and patient knowledge, appears to be both forward-looking and desirable directions for investigation.

Exploring the factors determining societal acceptance of AI applications in medical diagnostics is one of the potential areas for research exploration.

REFERENCES

Afifi-Sabet, K. *DeepMind's AI can Detect Eye Diseases as Accurately as World-Leading Doctors*. ITPro. 2018. Available online: https://www.itpro.co.uk/machine-learning (accessed on 15 November 2020).

Ahmad, Z., Rahim, S., Zubair, M., & Abdul-Ghafar, J. (2021). Artificial intelligence (AI) in medicine, current applications and future role with special emphasis on its potential and promise in pathology: present and future impact, obstacles including costs and acceptance among pathologists, practical and philosophical considerations. A comprehensive review. *Diagnostic pathology*, 16, 1-16. https://doi.org/10.1186/s13000-021-01085-4

Al Meslamani, A. Z. (2023). Applications of AI in pharmacy practice: a look at hospital and community settings. *Journal of Medical Economics*, *26*(1), 1081-1084. https://doi.org/10.1080/13696998.2023.2249758

Alberich-Bayarri, A., Pastor, A. J., González, R. L., & Castro, F. G. (2019). How to develop artificial intelligence applications. *Artificial intelligence in medical imaging: opportunities, applications and risks*, 49-59. https://doi.org/10.1007/978-3-319-94878-2_5

Asan, O., Bayrak, A. E., & Choudhury, A. (2020). Artificial intelligence and human trust in healthcare: focus on clinicians. *Journal of medical Internet research*, 22(6), e15154. https://doi.org/10.2196/15154

Awwalu, J., Garba, A. G., Ghazvini, A., & Atuah, R. (2015). Artificial intelligence in personalized medicine application of AI algorithms in solving personalized medicine problems. *International Journal of Computer Theory and Engineering*, 7(6), 439. https://doi.org/10.7763/IJCTE

Ayad, N., Schwendicke, F., Krois, J., van den Bosch, S., Bergé, S., Bohner, L., Hanisch, M., & Vinayahalingam, S. (2023). Patients' perspectives on the use of artificial intelligence in dentistry: a regional survey. *Head & Face Medicine*, 19(1), 1-10. https://doi.org/10.1186/s13005-023-00368-z

Bahakeem, B.H., Alobaidi, S.F., Alzahrani, A. S., et al. (2023). The General Population's Perspectives on Implementation of Artificial Intelligence in Radiology in the Western Region of Saudi Arabia. *Cureus 15(4)*, 37391. https://doi.org/ 10.7759/cureus.37391

Baig, M. M., GholamHosseini, H., Moqeem, A. A., Mirza, F., & Lindén, M. (2017). A systematic review of wearable patient monitoring systems–current challenges and opportunities for clinical adoption. *Journal of medical systems*, 41, 1-9. https://doi.org/10.1007/s10916-017-0760-1

Bilan, Y., Oliinyk, O., Mishchuk, H., & Skare, M. (2023). Impact of information and communications technology on the development and use of knowledge. *Technological Forecasting and Social Change*, *191*, 122519. DOI: 10.1016/j.techfore.2023.122519

Bizzego, A., Bussola, N., Chierici, M., Maggio, V., Francescatto, M., Cima, L., Cristoforetti, M., Jurman, G., & Furlanello, C. (2019). Evaluating reproducibility of AI algorithms in digital pathology with DAPPER. *PLoS computational biology*, 15(3), e1006269. https://doi.org/10.1371/journal.pcbi.1006269

Boiko, A., Zwolińska-Ligaj, M., Bozhenko, V., Florczak, E., & Ovcharenko, V. (2021). Readiness for implementing innovations in banking in advanced and emerging economies. *Journal of International Studies*, *14*(4), 236-250. doi:10.14254/2071-8330.2021/14-4/16

Chernobrivtseva, V., Misyurin, A. S. (2022). New technologies in radiology diagnostics. *Practical oncology*, https://www.doi.org/10.31917/2304203

Collins, G. S., & Moons, K. G. (2019). Reporting of artificial intelligence prediction models. *The Lancet*, 393(10181), 1577-1579. https://doi.org/10.1016/S0140-6736(19)30037-6

Cubric, M. (2020). Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study. *Technology in Society*, *62*, 101257. https://doi.org/10.1016/j.techsoc.2020.101257

Czemiel-Grzybowska W. (2022). Conceptualization and Mapping of Predictors of Technological Entrepreneurship Growth in a Changing Economic Environment (COVID-19) from the Polish Energy Sector, *Energies, 15(18),* 1-14, https://doi.org/10.3390/en15186543

Czemiel-Grzybowska W., Walicka M., Żemigała M., (2015). Technology entrepreneurship - state of the art and future challenges, *Eurasian Journal of Social Sciences, 3(4),* 10 21, https://doi.org/10.15604/ejss.2015.03.04.002

de Hond, A. A., Leeuwenberg, A. M., Hooft, L., Kant, I. M., Nijman, S. W., van Os, H. J., Aardoom, J. J., Debray, T. P. A., Schuit, E., van Smeden, M., Reitsma, J. B., Steyerberg, E. W., Chavannes, N. H., & Moons, K. G. (2022). Guidelines and quality criteria for artificial intelligence-based prediction models in healthcare: a scoping review. *NPJ digital medicine,* 5(1), 2. https://doi.org/10.1038/s41746-021-00549-7

Dicuonzo, G., Donofrio, F., Fusco, A., & Shini, M. (2023). Healthcare system: Moving forward with artificial intelligence. *Technovation*, *120,* 102510. https://doi.org/10.1016/j.technovation.2022.102510

Doanh, D. C., Dufek, Z., Ejdys, J., Ginevičius, R., Korzyński, P., Mazurek, G., Paliszkiewicz, J., Wach, K., & Ziemba, E. (2023). Generative AI in the manufacturing process: theoretical considerations. *Engineering Management in Production and Services,* 15(4), 76-89. https://doi.org/emj-2023-0029

Dreyer, K., & Allen, B. (2018). Artificial intelligence in health care: brave new world or golden opportunity?. *Journal of the American College of Radiology*, 15(4), 655-657. https://doi.org/10.1016/j.jacr.2018.01.010

Erickson, B. J., Korfiatis, P., Akkus, Z., & Kline, T. L. (2017). Machine learning for medical imaging. *Radiographics*, 37(2), 505-515. https://doi.org/10.1148/rg.2017160130

Esmaeilzadeh, P., Mirzaei, T., & Dharanikota, S. (2021). Patients' perceptions toward human–artificial intelligence interaction in health care: experimental study. *Journal of medical Internet research,* 23(11), e25856. https://doi.org/10.2196/25856

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature,* 542(7639), 115-118. https://doi.org/10.1038/nature21056

Eurostat, S. E. (2023). Population Projections in the EU, from https://ec.europa.eu/eurostat/statistics-explained/index.php?oldid=497115.

Florek, M., & Lewicki, M. (2022). Destinations, virtual reality and COVID-19. How isolation has shaped the behaviours and attitudes towards VR. *Economics and Sociology, 15*(1), 205-221. doi:10.14254/2071-789X.2022/15-1/13

Gaczek, P., Pozharliev, R., Leszczyński, G., & Zieliński, M. (2023). Overcoming consumer resistance to AI in General Health Care. *Journal of Interactive Marketing*, 58(2-3), 321-338. https://doi.org/10.1177/10949968221151061

Giannos, P. (2023). Evaluating the limits of AI in medical specialisation: ChatGPT's performance on the UK Neurology Specialty Certificate Examination. *BMJ Neurology Open,* 5(1). https://doi.org/10.1136/bmjno-2023-000451

Gifari, M. W., Samodro, P., & Kurniawan, D. W. (2021). Artificial intelligence toward personalized medicine. *Pharmaceut. Sci. Res,* 8(2), 1. https://doi.org/10.7454/psr.v8i2.1199

Gips, B., & Bahramisharif, A. (2022). *AI in Diagnostics*. Htttps://doi.org/10.14293/S2199-1006.1.SOR-.PPPCTUJO.v1

Gruenwald, L., Jain, S., & Groppe, S. (Eds.). (2021). *Leveraging artificial intelligence in global epidemics*. Academic Press.

Gulshan, V.; Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., Venugopalan, S., Widner, K., Madams, T., Cuadros, J., Kim, R., Raman, R., Nelson, P. C., Mega, J. L., & Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA network open, 316*(22), 2402-2410. https://doi.org/10.1001/jama.2016.17216

Halicka, K., & Gola, A. (2024). Gerontechnology ranking using the TOPSIS methods. Engineering Management in Produc tion and Services, 16(1), 93-103. https://doi.org/10.2478/emj-2024-0007

Hanhui, X. U. (2019). [知情同意] 視角下人工智能用於醫療診斷的透明度問題: The Problem of the Non-transparency of Artificial Intelligence Technologies in Medical Diagnosis: A View Based on Informed Consent. *International Journal of Chinese & Comparative Philosophy of Medicine*, 17(1), 49-58. https://doi.org/10.24112/ijccpm.171664

Harada, Y., Katsukura, S., Kawamura, R., & Shimizu, T. (2021). Efficacy of artificial-intelligence-driven differential-diagnosis list on the diagnostic accuracy of physicians: an open-label randomized controlled study. *International Journal of Environmental Research and Public Health*, 18(4), 2086. https://doi.org/10.3390/ijerph18042086

Hariri, R. H., Fredericks, E. M., & Bowers, K. M. (2019). Uncertainty in big data analytics: survey, opportunities, and challenges. *Journal of Big Data*, 6(1), 1-16. https://doi.org/10.1186/s40537-019-0206-3

Hashimoto, D. A., Rosman, G., & Meireles, O. R. (2021). *Artificial intelligence in surgery: understanding the role of AI in surgical practice*. McGraw Hill Professional.

Hashimoto, D. A., Rosman, G., Rus, D., & Meireles, O. R. (2018). Artificial intelligence in surgery: promises and perils. *Annals of surgery*, 268(1), 70. https://doi.org/10.1097/SLA.0000000000002693

Hsieh, P. J. (2023). Determinants of physicians' intention to use AI-assisted diagnosis: An integrated readiness perspective. *Computers in Human Behavior*, 147, 107868. https://doi.org/10.1016/j.chb.2023.107868

Hwang, E. J., Park, S., Jin, K. N., Im Kim, J., Choi, S. Y., Lee, J. H., Goo, J. M., Aum. J., Yim, J.-J., Cohen, J. G., Ferretti, G. R., & Park, C. M. (2019). Development and validation of a deep learning–based automated detection algorithm for major thoracic diseases on chest radiographs. *JAMA network open*, 2(3), e191095-e191095. https://doi.org/10.1001/jamanetworkopen.2019.1095

Ibba, S., Tancredi, C., Fantesini, A., Cellina, M., Presta, R., Montanari, R., Papa, S., Alì, M. (2023). How do patients perceive the AI-radiologists interaction? Results of a survey on 2119 responders, European Journal of Radiology, 165, 110917, https://doi.org/10.1016/j.ejrad.2023.110917.

Ikkatai, Y., Hartwig, T., Takanashi, N., & Yokoyama, H. M. (2022). Octagon measurement: Public attitudes toward AI ethics. *International Journal of Human–Computer Interaction*, 38(17), 1589-1606. https://doi.org/10.1080/10447318.2021.2009669

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2017). Artificial intelligence in healthcare: past, present and future. *Stroke and vascular neurology*, 2(4). https://doi.org/10.1136/svn-2017-000101

Juravle, G., Boudouraki, A., Terziyska, M., & Rezlescu, C. (2020). Trust in artificial intelligence for medical diagnoses. *Progress in brain research*, 253, 263-282. https://doi.org/10.1016/bs.pbr.2020.06.006

Kanegae, H., Suzuki, K., Fukatani, K., Ito, T., Harada, N., & Kario, K. (2020). Highly precise risk prediction model for new-onset hypertension using artificial intelligence techniques. *The Journal of Clinical Hypertension*, 22(3), 445-450. https://doi.org/10.1111/jch.13759

Kerasidou, C. X., Kerasidou, A., Buscher, M., & Wilkinson, S. (2022). Before and beyond trust: reliance in medical AI. *Journal of medical ethics*, 48(11), 852-856. https://doi.org/10.1136/medethics-2020-107095

Kieslich, K., Lünich, M., & Došenović, P. (2023). Ever heard of ethical AI? Investigating the salience of ethical AI issues among the German population. *International Journal of Human–Computer Interaction*, 1-14. https://doi.org/10.1080/10447318.2023.2178612

Kolozsvári, L. R., Bérczes, T., Hajdu, A., Gesztelyi, R., Tiba, A., Varga, Al-Tammemi, A. B., Szőllősi, G. J., Harsányi, S., Garbóczy, S., & Zsuga, J. (2021). Predicting the epidemic curve of the coronavirus (SARS-CoV-2) disease (COVID-19) using artificial intelligence: An application on the first and second waves. *Informatics in Medicine Unlocked*, 25, 100691. https://doi.org/10.1101/2020.04.17.20069666

Kulkov, I. (2021). The role of artificial intelligence in business transformation: A case of pharmaceutical companies. *Technology in Society*, *66*, 101629. https://doi.org/10.1016/j.techsoc.2021.101629

Laï, M. C., Brian, M., & Mamzer, M. F. (2020). Perceptions of artificial intelligence in healthcare: findings from a qualitative survey study among actors in France. *Journal of translational medicine*, 18(1), 1-13. https://doi.org/10.1186/s12967-019-02204-y

Lee, C. C., Czaja, S. J., Moxley, J. H., Sharit, J., Boot, W. R., Charness, N., & Rogers, W. A. (2019). Attitudes toward computers across adulthood from 1994 to 2013. *The Gerontologist*, 59(1), 22-33. https://doi.org/10.1093/geront/gny081

Lee, D., & Yoon, S. N. (2021). Application of artificial intelligence-based technologies in the healthcare industry: Opportunities and challenges. *International Journal of Environmental Research and Public Health*, 18(1), 271. https://doi.org/10.3390/ijerph18010271

Lee, J. W. (2010). The roles of demographics on the perceptions of electronic commerce adoption. *Academy of Marketing Studies Journal*, 14(1), 71-89.

Lee, S. M., & Lee, D. (2020). Healthcare wearable devices: an analysis of key factors for continuous use intention. *Service Business*, 14(4), 503-531. https://doi.org/10.1007/s11628-020-00428-3

Lewicki, A., Pancerz, K., & Puzio, L. (2021). The temporal inference with the use of ant-based clustering algorithm and flow graphs in the problem of prognosing complications of medical surgical procedures. *Human Technology, 17*(3), 213–234. https://doi.org/10.14254/1795-6889.2021.17-3.3

Litjens, G., Kooi, T., Bejnordi, B., Setio, A., Ciompi, F., Ghafoorian, M., van der Laak, J. A. W. M., van Ginneken, B., & Sánchez, C. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis,* 42, 60-88. https://doi.org/10.1016/j.media.2017.07.005

MacIntyre, C. R., Chen, X., Kunasekaran, M., Quigley, A., Lim, S., Stone, H., Paik, H., Yao, L., Heslop, D., Wei, W., Sarmiento, I., & Gurdasani, D. (2023). Artificial intelligence in public health: the potential of epidemic early warning systems. *Journal of International Medical Research*, 51(3), 03000605231159335. https://doi.org/10.1177/03000605231159335

Malche, T., Tharewal, S., Tiwari, P. K., Jabarulla, M. Y., Alnuaim, A. A., Hatamleh, W. A., & Ullah, M. A. (2022). Artificial intelligence of things-(aiot-) based patient activity tracking system for remote patient monitoring. *Journal of Healthcare Engineering*, 2022. https://doi.org/10.1155/2022/8732213

Mehta, N., Pandit, A., & Shukla, S. (2019). Transforming healthcare with big data analytics and artificial intelligence: A systematic mapping study. *Journal of biomedical informatics*, 100, 103311. https://doi.org/10.1016/j.jbi.2019.103311

Mishchuk, H., Bilan, Y., & Mishchuk, V. (2023). Employment risks under the conditions of the Covid-19 pandemic and their impact on changes in economic behaviour. *Entrepreneurial Business and Economics Review, 11*(2), 201-216. https://doi.org/10.15678/EBER.2023.110211

Morgan, C., Manson, T., Suresh, V., Govender, J., Jansson, D., Thomas, D., Shao, X., Wang, D., Günther, M., Dragunow, M., & Tippett, L. (2021). New and emerging magnetic resonance imaging techniques in mild cognitive impairment and Alzheimer's disease. *Brain Research New Zealand–Rangahau Roro Aotearoa*.

Murdoch, B. (2021). Privacy and artificial intelligence: challenges for protecting health information in a new era. *BMC Medical Ethics,* 22(1), 1-5. https://doi.org/10.1186/s12910-021-00687-3

Navarro, C. L. A., Damen, J. A., Takada, T., Nijman, S. W., Dhiman, P., Ma, J., Collins, G. S., Bajpai, R., Riley, R. D., Moons, K. G. M., & Hooft, L. (2021). Risk of bias in studies on prediction models developed using supervised machine learning techniques: systematic review. *bmj*, 375. https://doi.org/10.1136/bmj.n2281

Nolan, P. (2023). Artificial intelligence in medicine–is too much transparency a good thing?. *Medico-Legal Journal*, 00258172221141243. https://doi.org/10.1177/00258172221141243

Ongena, Y.P., Haan, M., Yakar, D., Kwee, T.C. (2020). Patients' views on the implementation of artificial intelligence in radiology: development and validation of a standardized questionnaire, *European Radiology, 30,* 1033-1040. https://doi.org/10.1007/s00330-019-06486-0

Parasher, G., Wong, M., & Rawat, M. (2020). Evolving role of artificial intelligence in gastrointestinal endoscopy. *World journal of gastroenterology,* 26(46), 7287. https://doi.org/10.3748/wjg.v26.i46.7287

Park, Y. J., Cho, H. S., & Kim, M. N. (2023). AI Model for Detection of Abdominal Hemorrhage Lesions in Abdominal CT Images. *Bioengineering,* 10(4), 502. https://doi.org/10.3390/bioengineering10040502

Pishnyak, A., Khalina, N. (2021) Perception of New Technologies: Constructing an Innovation Openness Index. *Foresight and STI Governance, 15(1),* 39-54. https://doi.org/10.17323/2500- 2597.2021.1.39.54

Poon, A. I., & Sung, J. J. (2021). Opening the black box of AI-Medicine. *Journal of Gastroenterology and Hepatology*, 36(3), 581-584. https://doi.org/10.1111/jgh.15384

Richardson, J. P., Smith, C., Curtis, S., Watson, S., Zhu, X., Barry, B., & Sharp, R. R. (2021). Patient apprehensions about the use of artificial intelligence in healthcare. *NPJ digital medicine*, 4(1), 140. https://doi.org/10.1038/s41746-021-00509-1

Rigby, M. J. (2019). Ethical dimensions of using artificial intelligence in health care. *AMA Journal of Ethics*, 21(2), 121-124. https://doi.org/10.1001/amajethics.2019.121

Robinson, S.C. (2020). Trust, transparency, and openness: How inclusion of cultural values shapes Nordic national public policy strategies for artificial intelligence (AI). *Technology in Society*, *63*, 101421. https://doi.org/10.1016/j.techsoc.2020.101421

Romero-Brufau, S., Wyatt, K. D., Boyum, P., Mickelson, M., Moore, M., & Cognetta-Rieke, C. (2020). A lesson in implementation: a pre-post study of providers' experience with artificial intelligence-based clinical decision support. *International journal of medical informatics*, 137, 104072. https://doi.org/10.1016/j.ijmedinf.2019.104072

Rong, Y., Castner, N., Bozkir, E., & Kasneci, E. (2022). User Trust on an Explainable AI-based Medical Diagnosis Support System. *arXiv preprint arXiv:2204.12230*. https://doi.org/10.48550/arXiv.2204.12230

Rubinic, I., Kurtov, M., Rubinic, I., Likic, R., Dargan, P. I., & Wood, D. M. (2023). Artificial Intelligence in Clinical Pharmacology: A Case Study and Scoping Review of Large Language Models and Bioweapon Potential. *British Journal of Clinical Pharmacology*. https://doi.org/10.1111/bcp.15899

Saleh, G. A., Batouty, N. M., Haggag, S., Elnakib, A., Khalifa, F., Taher, F., Mohamed, M. A., Farag, R., Sandhu, H., Sewelam, A., & El-Baz, A. (2022). The role of medical image modalities and AI in the early detection, diagnosis and grading of retinal diseases: a survey. *Bioengineering*, 9(8), 366. https://doi.org/10.3390/bioengineering9080366

Schork, N. J. (2019). Artificial intelligence and personalized medicine. *Precision medicine in Cancer therapy*, 265-283. https://doi.org/10.1007/978-3-030-16391-4_11

Sengupta, P. P., & Chandrashekhar, Y. S. (2021). Building trust in AI: opportunities and challenges for cardiac imaging. *Cardiovascular Imaging*, 14(2), 520-522. https://doi.org/10.1016/j.jcmg.2021.01.002

Shaik, T., Tao, X., Higgins, N., Li, L., Gururajan, R., Zhou, X., & Acharya, U. R. (2023). Remote patient monitoring using artificial intelligence: Current state, applications, and challenges. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 13(2), e1485. https://doi.org/10.1002/widm.1485

Shen, D., Wu, G., & Suk, H. I. (2017). Deep learning in medical image analysis. *Annual review of biomedical engineering*, 19, 221-248. https://doi.org/10.1146/annurev-bioeng-071516-044442

Sidey-Gibbons, J. A., & Sidey-Gibbons, C. J. (2019). Machine learning in medicine: a practical introduction. *BMC medical research methodology*, 19, 1-18. https://doi.org/10.1186/s12874-019-0681-4

Sitthipon, T., Kaewpuang, P., Jaipong, P., Sriboonruang, P., Siripipattanakul, S., & Auttawechasakoon, P. (2022). Artificial Intelligence (AI) Adoption in the Medical Education during the Digital Era: A Review Article. *Review of Advanced Multidispliniary Science, Engineering & Innovation*, 1(2), 1-7.

Sohn, K., Kwon, P. (2020). Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products, *Telematics Informatics, 47,* 101324. https://doi.org/10.1016/j.tele.2019.101324.

Sone, K., Toyohara, Y., Taguchi, A., Miyamoto, Y., Tanikawa, M., Uchino-Mori, M., Iriyama, T., Tsuruga, T., & Osuga, Y. (2021). Application of artificial intelligence in gynecologic malignancies: A review. *Journal of Obstetrics and Gynaecology Research*, 47(8), 2577-2585. https://doi.org/10.1111/jog.14818

Stai, B., Heller, N., McSweeney, S., Rickman, J., Blake, P., Vasdev, R., Edgerton, Z., Tejpaul, R., Peterson, M., Rosenberg, J., Kalapara, A., Regmi, S., Papanikolopoulos, N., & Weight, C. (2020). Public perceptions of artificial intelligence and robotics in medicine. *Journal of endourology*, 34(10), 1041-1048. https://doi.org/10.1089/end.2020.0137

Sushma, M., Goud, B. Y., Nikhil, M., & Reddy, G. S. K. (2021, May). AI Medical Diagnosis Application. In *2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS)* (pp. 1710-1716). IEEE. https://doi.org/10.1109/ICICCS51141.2021.9432301

Taylor, N. Duke Report Identifies Barriers to Adoption of AI Healthcare Systems. *MedTech Dive*. 2019. Available online: https://www.medtechdive.com/news/duke-report-identifies-barriers-to-adoption-of-ai-healthcare-systems/546739/ (accessed on 15 November 2020).

Tran, A. Q., Nguyen, L. H., Nguyen, H. S. A., Nguyen, C. T., Vu, L. G., Zhang, M., Vu, T. M. T., Nguyen, S. H., Tran, B. X., Latkin, C. A., Ho, R. C. M., & Ho, C. S. H. (2021). Determinants of intention to use artificial intelligence-based diagnosis support system among prospective physicians. *Frontiers in public health*, 9, 755644. https://doi.org/10.3389/fpubh.2021.755644

Tucci, V., Saary, J., & Doyle, T. E. (2022). Factors influencing trust in medical artificial intelligence for healthcare professionals: A narrative review. *Journal of Medical Artificial Intelligence*, 5. https://doi.org/10.21037/jmai-21-25

Turja, T., Aaltonen, I., Taipale, S., & Oksanen, A. (2020). Robot acceptance model for care (RAM-care): A principled approach to the intention to use care robots. *Information & Management*, 57(5), 103220. https://doi.org/10.1016/j.im.2019.103220

United Nations, Department of Economic and Social Affairs, Population Division (2019). World Population Prospects 2019: Data Booket. ST/ESA/SER.A/424, from https://population.un.org/wpp2019/Publications/Files/WPP2019_DataBooklet.pdf.

Uzialko, A. (2019). Artificial Intelligence Will Change Healthcare as We Know it. *Business News Daily*, 9.

van Ooijen, P. M. (2019). Quality and curation of medical images and data. *Artificial Intelligence in Medical Imaging: Opportunities, Applications and Risks*, 247-255. https://doi.org/10.1007/978-3-319-94878-2_17

Wach, K., Duong, C. D., Ejdys, J., Kazlauskaitė, R., Korzynski, P., Mazurek, G., Paliszkiewicz, J., & Ziemba, E. (2023). The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. *Entrepreneurial Business and Economics Review*, 11(2), 7-30. https://doi.org/10.15678/EBER.2023.110201

Wehbe, Y., Al Zaabi, M., & Svetinovic, D. (2018, November). Blockchain AI framework for healthcare records management: constrained goal model. In *2018 26th Telecommunications forum (TELFOR)* (pp. 420-425). IEEE. https://doi.org/10.1109/TELFOR.2018.8611900

Wolf, I., Levi, S., & Lopez del Rio, L.C. Y (2021). Moving toward funded pension scheme: Pure economic argument due to population aging or responsibility abdication of governments?. *Economics and Sociology*, *14*(4), 151-166. doi:10.14254/2071-789X.2021/14-4/9

Yanagawa, M., Niioka, H., Kusumoto, M., Awai, K., Tsubamoto, M., Satoh, Y., Miyata, T., Yoshida, Y., Kikuchi, N., Hata, A., Yamasaki, S., Kido, S., Nagahara, H., Miyake, J., & Tomiyama, N. (2021). Diagnostic performance for pulmonary adenocarcinoma on CT: comparison of radiologists with and without three-dimensional convolutional neural network. *European Radiology*, 31, 1978-1986. https://doi.org/10.1007/s00330-020-07339-x

Young, A. T., Amara, D., Bhattacharya, A., & Wei, M. L. (2021). Patient and general public attitudes towards clinical artificial intelligence: a mixed methods systematic review. *The Lancet Digital Health*, 3(9), e599-e611. https://doi.org/10.1016/S2589-7500(21)00132-1

Zhang, Z., Genc, Y., Xing, A., Wang, D., Fan, X., & Citardi, D. (2020). Lay individuals' perceptions of artificial intelligence (AI)-empowered healthcare systems. *Proceedings of the Association for Information Science and Technology*, 57(1), e326. https://doi.org/10.1002/pra2.326

Zhavoronkov, A., Vanhaelen, Q., & Oprea, T. I. (2020). Will artificial intelligence for drug discovery impact clinical pharmacology?. *Clinical Pharmacology & Therapeutics*, *107*(4), 780-785. https://doi.org/10.1002/cpt.1795

Zhou, Q., Zuley, M., Guo, Y., Yang, L., Nair, B., Vargo, A., Ghannam, S., Arefan, D., & Wu, S. (2021). A machine and human reader study on AI diagnosis model safety under attacks of adversarial images. *Nature communications*, 12(1), 7281. https://doi.org/10.1038/s41467-021-27577-x

Zhou, X. Y., Guo, Y., Shen, M., & Yang, G. Z. (2020). Application of artificial intelligence in surgery. *Frontiers of medicine*, 14, 417-430. https://doi.org/10.1007/s11684-020-0770-0

Authors' Note

The research leading to these results has received funding from the commissioned task entitled "VIA CARPATIA Universities of Technology Network named after the President of the Republic of Poland Lech Kaczyński" contract no. MEiN/2022/DPI/2575 of 20.10.2022 action entitled In the neighborhood - inter-university research internships and study visits.

All correspondence should be addressed to
Joanna Ejdys
Bialystok University of Technology
15-351 Bialystok, ul. Wiejska 45A, Poland
j.ejdys@pb.edu.pl

Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology

https://ht.csr-pub.eu/

office@csr-pub.eu

Submissions:
https://ht.csr-pub.eu/index.php/ht/about/submissions