HUMAN TECHNOLOGY

ISSN: 1795-6889

https://ht.csr-pub.eu Volume 17(3), December 2021, 294-320

DETERMINANTS OF THE ADOPTION OF AI WEARABLES - PRACTICAL IMPLICATIONS FOR MARKETING

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Abstract: *Wearables have become a natural element of human life, determining our way of perceiving, understanding and experiencing the world. Enriched with elements of artificial intelligence, they will change our habits and draw us into the digital dimension of the world - a space of uninterrupted interaction between people and technology. As a result, there are still new ideas for the effective use of AI wearables in the consumer space. The main aim of the article is to examine the determinants behind the acceptance of the AI wearables, with particular emphasis on the strength and nature of the relationship between the consumer and technology. The UTAUT2 model is used for this purpose. The article is a continuation of the previous reflections and analyses in this area; at the same time it constitutes an initial stage of research on the issues related to the adoption of AI wearables.*

Keywords: *wearable technology, artificial intelligence, consumer, augmented intelligence, marketing.*

DOI: https://doi.org/10.14254/1795-6889.2021.17-3.6

INTRODUCTION

The issues related to human and AI-related technology are increasingly popular among researchers. Although the concept of artificial intelligence itself was already defined in the 1950s, the first publications on human and AI-related technology could only be found in 1983. In order to identify the current breadth of knowledge and the main directions of research in the field of human and AI-related technology, a systematic literature review was conducted. It covered three key areas: 1) determination of key databases and collection of publications, 2) selection and development of a complete publication database, and 3) bibliometric and content analysis.

In the first stage, the databases were selected using the availability of full text as a criterion. Thus, six studied international databases included Ebsco, Elsevier, Emerald, Web of Science, Scopus, Wiley, analysis of which allowed for the identification of over 4,000 publications on human and AI-related technology (full-text and peer-reviewed publications; human and AI-related technology in the title, abstract, keywords; repeated publications were removed). At this stage, it was decided not to limit the database to only social sciences but to also encompass publications in the field of engineering and technical sciences, medicine, humanities, as well as natural sciences. As part of the methodology of a systematic literature review, a number of publications from particular years were analysed.

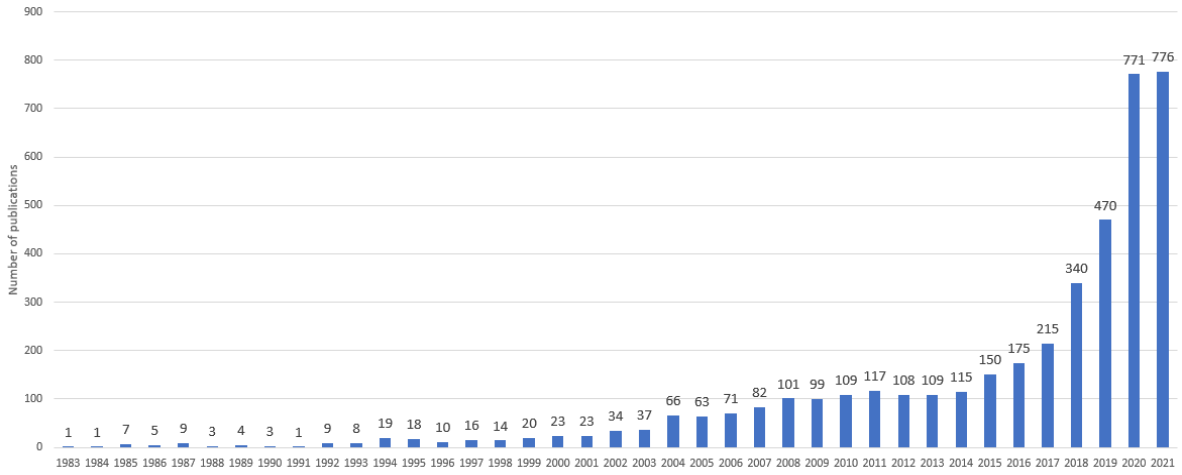

Figure 1. Analysis of the number of publications from particular years.
[Source: own study]

This allowed for the conclusion that the issues of human and AI-related technology are popular among researchers, and the rapid growth of interest has been observed since 2019. It seems fully justified due to the increasing possibilities of market implementation of solutions based on artificial intelligence, as well as their economic, legal and socio-cultural impact, which leads to the emergence of numerous scientific and research gaps. Taking into account, on the one hand, the indicated dynamics of the number of publications, and on the other hand, the intensity of the observed economic and socio-cultural changes caused by the implementation of AI in market practice, further analyzes were focused on the last 10 years.

The list of disciplines dealing with the issues of human and AI-related technology is very wide. Most publications in the analyzed area concerned Computer Science, Medicine, Engineering, Mathematics and Biochemistry, Genetics. However, the Field-Weighted Citation Impact analysis shows that it was the highest for publications in the field of Energy (2.86), Social Sciences (2.69), Business, Management and Accounting (2.68), Physics and Astronomy (2, 67), Arts and Humanities (2.28).

The obtained publication base was analyzed using bibliometric techniques. An analysis of keyword frequency and research problems was performed. Selected keywords related to the phrase of human and AI-related technology were subjected to quantitative analysis. At the same time, the visualization of attendance was presented in the form of a "word cloud", where the frequency of occurrence was reflected in the size and thickness of the font (Figure 2).

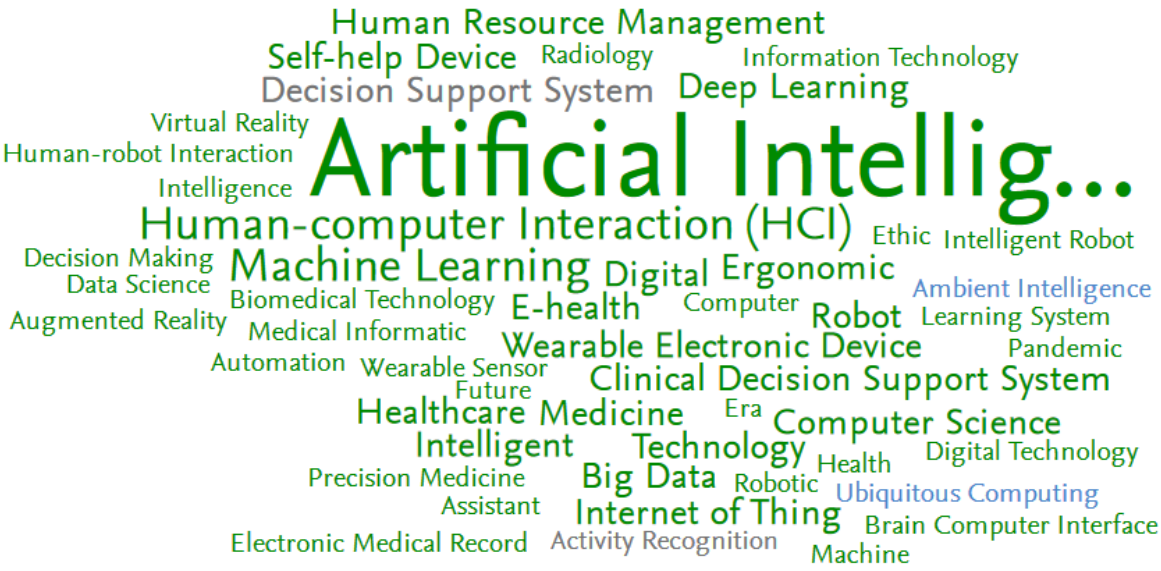

Figure 2. Keyword frequency analysis for: human and AI-related technology (2010 - 2021). [Source: own study]

The most frequently appearing keywords are, obviously, artificial intelligence (increase in the number of publications in the analyzed period = +447.7%), Machine Learning (increase in the number of publications in the analyzed period = +3,450), Wearable Electronic Device (increase in the number of publications in the analyzed period = + 3.100%), Human-computer Interaction (increase in the number of publications in the analyzed period = +281.8%), Healthcare (increase in the number of publications in the analyzed period = +2.800%).

In spite of the fact that the issues of human and AI-related technology are capturing the interest of researchers practically all over the world, the analysis of the number of publications taking into account individual countries showed that the most active in this area are the United States, China, the United Kingdom, Germany and India (Figure 3).

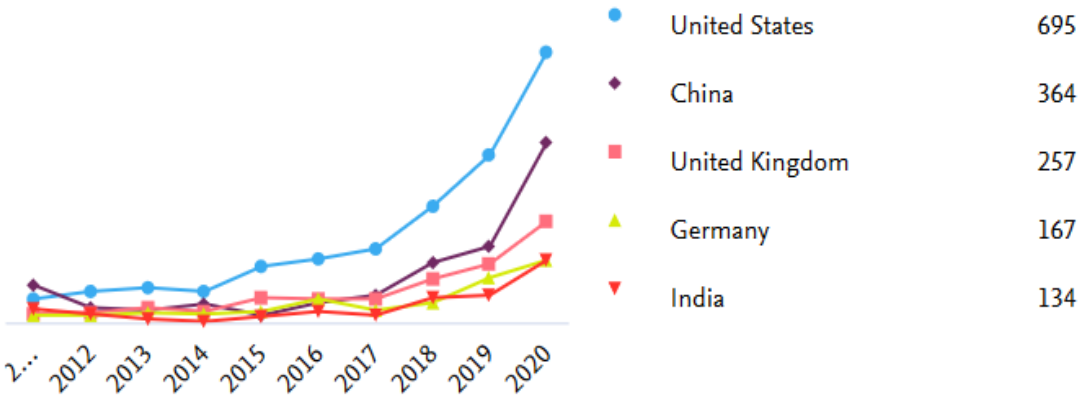

Figure 3. The most active countries in terms of the number of publications for the phrase: human and AI-related technology (2010 – 2021).
[Source: own study]

This does not seem surprising, given the current position and strategy of these countries in the field of the development of digital technologies, especially artificial intelligence and building their economic position in the world on this base.

American and European universities have the largest percentage contribution to the development of knowledge in the field of human and AI-related technology in this period, which may be related to the current level of economic development and the amount of expenditure they allocate to research on AI and its new potential applications, including also increasing the degree of commercialization of the findings (Figure 4).

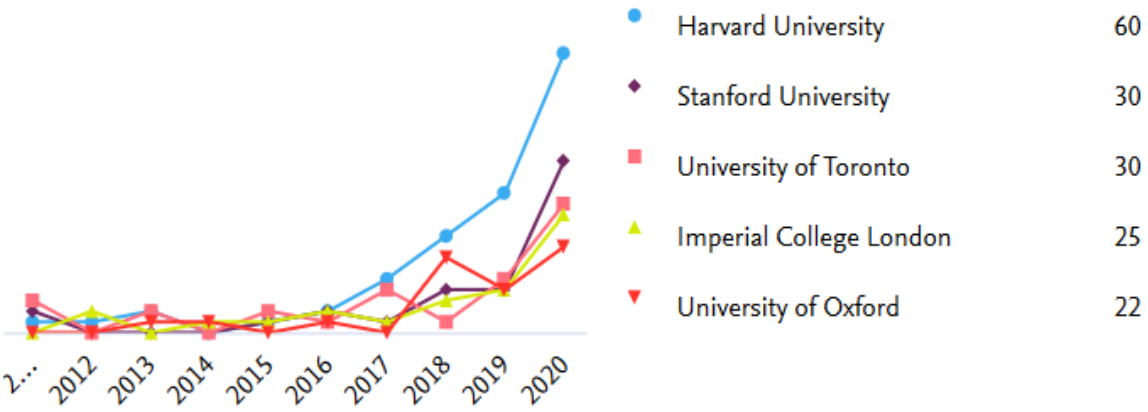

Figure 4. The most active scientific and research institutions according to the number of publications for the phrase: human and AI-related technology (2010 – 2021).
[Source: own study]

The highest level of citation rate of authors dealing with the issues of human and AI-related technology and their field-weighted citation impact was also analyzed. The authors that prevail here come from the United States of America and the United Kingdom (Table 1).

Table 1. The most frequently cited authors dealing with the issues of human and AI-related technology (2010 – 2021).

Author	Affiliation	Country/Region	Field-Weighted Citation Impact	Citation Count
Roggen, Daniel	University of Sussex	United Kingdom	30,70	1385
Lo, Benny	Imperial College London	United Kingdom	22,40	601
Cook, Dianie J.	Washington State University Pullman	United States	16,44	502
Acampora, Giovanni	National Institute for Nuclear Physics	Italy	16,27	439
Yang, Guangzhong	Imperial College London	United Kingdom	15,53	626
Kohane, Isaac S.	Harvard University	United States	11,02	437
Yu, Kun Hsing	Harvard University	United States	11,02	437
Aerts, Hugo J.W.L.	Maastricht University	Netherlands	12,5	372
Rahwan, Iyad	Massachusetts Institute of Technology	United States	10,26	573
Floridi, Luciano	Queen Mary University of London	United Kingdom	10,08	296
Taddeo, Mariarosaria	Queen Mary University of London	United Kingdom	10,08	296

Subsequently, the conducted analysis was limited to the areas related to the category of Business, Management and Accounting, which is the area of interest of the authors, which allowed for the possibility to distinguish key research perspectives and indicate those areas of human and AI-related technology that require further exploration. The total number of publications in human and AI-related technology in the category: Business, Management and Accounting in the analyzed period was 74, and its Field-Weighted Citation Impact was 2.68. The analysis of the frequency of keywords related to human and AI-related technology in the category: Business, Management and Accounting and their quantitative analysis presented in the form of a "word cloud", where the frequency of occurrence was reflected in the size and thickness of the font (Figure 5), indicated that the key word in the group of the top five most popular keywords is artificial intelligence, where the increase in the number of publications in the analyzed period was +84.6%. The analysis of the remaining keywords showed the maintenance of a constant number of publications concerning the words: robot and ethics (no changes noted in this respect), as well as a significant decrease in the number of publications concerning: human resource management and philosophical aspect (in each case the indicator = -100%).

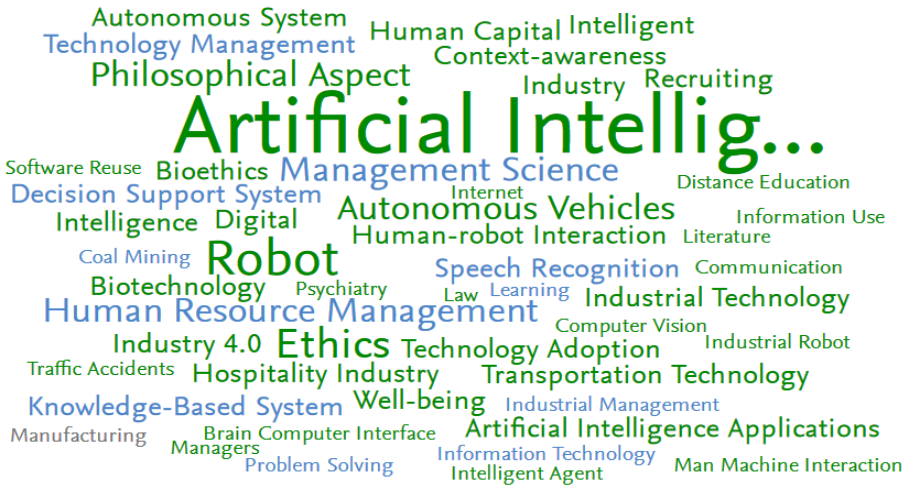

Figure 5. Keyword frequency analysis for human and AI-related technology for the category: Business, Management and Accounting (2010 – 2021).
[Source: own study]

The results of the analysis of the number of publications on human and AI-related technology in the category: Business, Management and Accounting, taking into account individual countries, showed that China, the United States and the United Kingdom are the most active in this respect. The research in this area is an important field of interest for the work of the University of Oxford, Queen Mary University of London, Henan Polytechnic University, University College London and the University of Birmingham. The analysis of the thematic areas of publications concerning the phrase: human and AI-related technology in the category: Business, Management and Accounting showed that the highest percentage was related to the Management of Technology and Innovation, slightly over 34% of publications. The smallest number of publications concerned Marketing 3.4% and Tourism, Leisure and Hospitality Management 2.3%.

At the same time, however, the analysis of the number of citations indicated that the highest value of the Field-Weighted Citation Impact indicator was achieved for publications in the field of Tourism, Leisure and Hospitality Management. Subsequently, it concerns Business and International Management, Management of Technology and Innovation and Marketing (Table 2).

Table 2. Field-Weighted Citation Impact indicator in individual thematic areas regarding the phrase: human and AI-related technology in the category: Business, Management and Accounting (2010 – 2021).

Subject area	Field-Weighted Citation Impact	Citation Count
Tourism, Leisure and Hospitality Management	18.92	163
Business and International Management	3.23	291
Management of Technology and Innovation	3.19	619
Marketing	2.92	53
Strategy and Management	1.96	111
General Business, Management and Accounting	1.87	69
Management Information Systems	1.40	107
Accounting	0.49	8

Then, an analysis of the citations of individual publications was conducted in order to assess their impact on further research (Table 3).

Table 3. The most frequently cited publications concerning the phrase: human and AI-related technology in the category: Business, Management and Accounting (2010 – 2021).

Title	Authors	Year	Source title	Cited by	Author Keywords
Applied artificial intelligence and trust-The case of autonomous vehicles and medical assistance devices	Hengstler M., Enkel E., Duelli S.	2016	Technological Forecasting and Social Change vol. 105	195	Artificial intelligence; Automation; Autonomous driving; Autonomous vehicle; Medical assistance; Trust
From high-touch to high-tech: COVID-19 drives robotics adoption	Zeng Z., Chen P.-J., Lew A.A.	2020	Tourism Geographies Vol.22 no. 3	143	Artificial Intelligence; COVID-19 pandemic; drones; high-tech; high-touch; human-robot interaction; Robotics
Artificial Intelligence and the 'Good Society': the US, EU, and UK approach	Cath C., Wachter S., Mittelstadt B., Taddeo M., Floridi L.	2018	Science and Engineering Ethics vol.24, no.2	134	Algorithms; Artificial intelligence; Data ethics; Good society; Human dignity
Ethical Design of Intelligent Assistive Technologies for Dementia: A Descriptive Review	Ienca M., Wangmo T., Jotterand F., Kressig R.W., Elger B.	2018	Science and Engineering Ethics vol. 24, no. 4	57	Artificial intelligence; Assistive technology; Dementia; Ethical design; Neurotechnology; Proactive ethics; User-centered
The Ugly Truth About Ourselves and Our Robot Creations: The Problem of Bias and Social Inequity	Howard A., Borenstein J.	2018	Science and Engineering Ethics vol. 24, no. 5	55	Artificial intelligence; Design ethics; Implicit bias; Professional ethics; Robot ethics

Among the five most cited publications in the analyzed period for the phrase of human and AI-related technology in the category: Business, Management and Accounting, the issues of trust and ethics were mainly addressed, which is reflected in intensive efforts to build a uniform legal framework for the implementation of solutions based on AI within the EU, UNESCO or OECD.

The analysis of the collected material clearly indicates the topicality of research on issues related to human and AI-related technology, including the following categories: Business, Management and Accounting. This subject has been intensively undertaken by researchers representing various scientific disciplines, especially in the last 2-3 years. The multiplicity and differentiation of the topics related to human and AI-related technology, on the one hand, result in a desire for a holistic approach to the issues discussed, on the other, due to their complexity and multithreading, an increasing need to place them in a narrowly defined context emerges.

The conducted analysis showed that wearables are one of the most frequently appearing keywords related to the issues of human and AI-related technology research. At the same time research on the level of their social acceptance is still little known, and in the context of enriching wearables with completely new functionalities resulting from the implementation of AI which justifies the need for research in this area.

The main goal of the article is to identify factors influencing the acceptance process of AI wearables, with particular emphasis on the current research issues in human and AI related technology. In this regard, the UTAUT2 model (Venkatesh et al., 2012) was used, which is an extended unified theory of technology acceptance and use, with strong empirical justification. This article presents the experiences of consumers resulting from their previous interactions with wearables, including the assessment of the possibility of enrichment with AI-based solutions, which is part of the discourse on human and AI-related technology and contributes to expanding the current knowledge on this subject.

In order to achieve the research objectives, the following structure of the work was adopted: a review of the literature on the theoretical foundations of wearables and their possibilities, with particular emphasis on the consumer dimension, the UTAUT 2 model, hypotheses, methodology of the research, presentation of the results of the structural model, and finally, a discussion and identification of the theoretical and practical implications. Limitations to the conducted research were also taken into account.

Wearable Technology in Consumers' Life

Wearable technology refers to all kinds of advanced electronic devices or computers that are integrated with clothing and accessories used by people or their bodies, and that provides personalized functionalities (Oinas-Kukkonen, 2013; Wright & Keith, 2014; Choi and Kim, 2016; Vaitkevičius et al., 2019). These include electronic devices, software, data transmitters, and sensors that are part of clothing, jewelry, and body-worn accessories (Liu et al., 2016; Wright & Keith, 2014). Wearable devices are able to provide measurement and analysis of physiological and psychological data (Spagnolli et al., 2014), communication, two-way data exchange between a person and their environment (Kalantari, 2017, Fang & Chang, 2016), using applications installed in wearables or other related to mobile external devices (Muaremi et al., 2013). The wearable technology is based on wireless communication with the Internet or other devices, allowing access to information, including in real time (Park et al., 2014; Liu & Guo, 2017). Using various types of sensors, information is collected about consumers, analyzed, and then stored in appropriate applications. Wearables cover a wide range of devices, such as the currently popular smartwatches, smart bands, headphones, as well as glasses, including sunglasses, smart clothing and jewelry (non-invasive solutions) (Chuah et al., 2016; Chen et al., 2016). There are also increasingly innovative and futuristic solutions, such as: electronic skin patches as well as smart chest straps, contact lenses, electronic skin products or smart patches. There is also talk of the possibility of direct implementation of wearables into the human body, e.g. in the form of chips (invasive solutions). Wearables can be classified based on their form and purpose (to be worn on the head, e.g. a helmet, body e.g. clothing, hand e.g. smartwatch, jewelry) or their functions (e.g. monitoring a healthy lifestyle, information support etc.) (Mewara et al. 2016). A more complex taxonomy of wearables includes a number of features of these types of devices: the scope of functionality (monofunctional versus multifunctional), the level of invasiveness (invasive versus non-invasive), character (active versus passive), communication mode, area (sector, industry) applications and possibilities of their use (disposable versus reusable) (Park et al.,2014).

Wearables have an increasingly wider range of applications, hence solutions based on wearable technology can be found, for example, in medicine, care for seniors and young

children, the army, sport, trade, marketing, video games or at workplaces. The attributes of wearables determine the level of their usefulness in individual market sectors. According to Mewara, these attributes are both physical (lightweight, aesthetically pleasing, invisible, shape conformable) and functional (multi-functional, configurable, responsive and a bandwidth to enable the degree of interactivity) (Mewara et al. 2016).

It is estimated that global consumer spending on wearables will exceed $ 90 billion in 2022 (https://www.statista.com/topics/1556/wearable-technology) although this market is still very far from its saturation level. The analysis of trends on the wearables market allows for the assumption that its dynamics will be significantly accelerated by the parallel development of technologies such as artificial intelligence and 5G, which will increase the wearables' computing power and enable more accurate measurements, improving the reliability of the results provided. The possibility of increasing miniaturization of wearables is also important. Gartner predicts that by 2024 the possibilities of miniaturization will increase to such an extent that 10% of all such devices will be invisible to the user (Rimol, 2021). Undoubtedly, wearables will evolve in terms of their form (size, offered functionalities, intuitiveness, durability, design), which are becoming more desirable in order to satisfy consumer needs and to increase interaction with the devices. This has an impact on deepening existing behavioral experiences and constantly creating new forms of behavior (Oh & Kang, 2021; Lunney et al., 2016).

The wearables market is not homogeneous, both in terms of the manufacturers (e.g. Apple, Xiaomi, Huawei, Samsung)(https://www.idc.com/promo/wearablevendor) and the available products that have different levels of technological advancement and the possibilities that are on offer to the consumers. This entails a number of security challenges (in particular, data collection, management, processing and possible sharing, but also product defect and liability) and privacy (Gao et al., 2015). Moreover, regulations in this regard may differ from country to country or region to country around the world (Garattini et. Al, 2019). The issue of ethical considerations is also important (potential risk of manipulation, limiting choices, crossing the border of technology interference in customers' lives and their perception in society). It is more than just a product that meets a specific need. "It is a manifesto that allows you to define yourself and others in a given group through the symbolic meaning of a given device" (Hajo & Galinsky, 2012; Oh & Kang, 2021). In such an approach, wearables become a symbol of the customers' identity, reflecting their attitude towards the world and people. This may result in the lack of trust in a given solution or even discomfort resulting from its use and lead to technophobia in relation to a given device or technology or the effects resulting from its use. However, research shows that the role of trust varies depending on the context. It increases in a situation perceived by the consumer as crucial, e.g. health (Dierks, 2007), and is of little importance in normal or safe contexts (Esmaili et al., 2011).

Augmented Intelligence of the Customer

Wearables combine physical space (real world) and cyberspace through maximum use of technology, leading to building hyper-intelligence based on the multiplication of the effects of its synergy with humans. Undoubtedly, the development of new technologies, especially AI, is now perceived as a natural sequence of further consumer evolution. It is a vision of integrating new technologies and solutions based on them from various fields for the benefit of mankind (Holroyd, 2020). Artificial intelligence combines elements of computer science, cognitive

science and logic. It is aimed at recreating and improving human behavior. Among other things, algorithms can identify specific functions and patterns of behavior, and then learn them, stimulate them and improve their own actions. (Ertel, 2017). It has the ability to support customers - it plays an auxiliary role, strengthens human intelligence, not replace it (Crigger & Khoury, 2019; Hebbar, 2017), which leads to a gradual blurring of the boundary between artificial and human intelligence, creating a space for the so-called Augmented Intelligence of a human. Technology determines the way of perceiving the world, experiencing and feeling, while providing many interactive tools to deepen and broaden these experiences.

Artificial intelligence (AI), understood as models of human behavior and solutions allowing for the simulation of these behaviors, can be perceived in cognitive categories (I deepen my knowledge, I know more) or in human behavioral categories (efficiency of implemented activities versus perfect reproduction of human behavior, adaptability) (Russell & Norvig, 2016). Therefore, it refers to the effective analysis of huge databases, processing data into knowledge that is then used to generate behaviors based on it, which makes AI able to mimic a human (Jarrahi, 2018).This leads to wearables becoming more effective (Hoffman & Novaka, 2015). AI wearables, acting proactively, create a space for real-time integration of the obtained data. The devices are able to detect consumer activity while providing specific, necessary information at a given moment without the need to perform additional activities (e.g. logging into the system). They record everything happens around them and at the same time outside them, providing a new digital environment. The resulting data stream allows the discovery of a number of consumer behavior patterns. This translates into a change in these behaviors or leads to the remodeling of the cause and effect processes that determine the different behaviors, e.g. through a system of digital prompts that the consumer receives on an ongoing basis (steps taken, stress level, number of calories burned, missed calls, etc.) in accordance with their daily life cycle, which improves the individual management style (Shin et.al., 2019). This changes the performance of people's daily activities and affects the way people live, travel, learn,work and spend free time (Chen, 2012), although skeptics have doubts as to whether this change is long-term. Thanks to technological support, a customer knows more, understands the occurring cause-effect relationships much better, is able to predict more accurately, and the processes are conducted much faster and more efficiently. This leads to an increase in their cognitive abilities (Lisboa, 2018; Sharma, 2019). "We stimulate and release the possibilities of the human mind that have not been available to us so far" (Corrigan, 2012; Pasquinelli, 2015; Von Ahn, 2013).

Therefore, Augmented Intelligence aims to support and strengthen customer intelligence as an effect of its synergy with AI, in which there is mutual complementation and coexistence (complementarity) in a manner beneficial to both parties (Rold, 2019). "Humans and machines can go hand in hand" (Kotler et al., 2021). This continuous process makes the technology's ability to provide new benefits unlimited, and it constantly develops while stimulating customer development. So, digital transformation affects technology as much as people (Kane, 2019). Man and technology are then an inseparable whole (Mann, 2014). The resulting customer - technology interface enables interaction and cooperation in a specific context, while affecting the level of efficiency of the tasks (Xiong et al., 2021). This allows for things to be done that were not possible before. As a result, AI wearables can become more attractive to the customer, making it easier and more effective (Hoffman and Novak, 2015). They are becoming increasingly useful in everyday activities. Despite the enormous potential and added value

created by the synergy of AI and wearables, an opinion exists that this is only a form of luxury that will be of little use in the future.

Experts believe that the size of the global AI wearables market will reach USD 38.3 billion by 2025, which results, on the one hand, from a wide range of benefits they offer, and on the other hand, from the dynamics of AI development. At the same time, concerns are raised by the fact that, as Gartner experts identify, by 2023 the behavior of approximately 40% of the world's population will be digitally "tracked", and the information derived will become the basis for predicting and proactively creating social behavior. This intensifies the debate on privacy, security and ethics in the tech world, taking into account the fundamental rights of the consumer, especially when the status of previous technologies is undermined by successive digital innovations (Jouhki, 2020). The evolutionism of such an approach sets the directions for the development and adaptation of a human being and a consumer, assuming that under the influence of technology, and as a result of interaction with it, it changes over time, also changing its environment at the same time. As a result, the rapid development of Augmented Intelligence resulting from the implementation of AI wearables is possible only on the condition of understanding its essence and increasing social acceptance in this area (Xia and Maes, 2013).

Social Acceptance of AI Wearables

Acceptance of technologies and based solutions is a manifestation of the consumer's attitude. It is important both for the declared and implemented behaviors and influences their further development as an individual (Venkatesh & Davis, 2000). These behaviors are the result of the cognitive process and may lead to the acceptance, use or negation and rejection of individual solutions (Venkatesh & Brown, 2005). Acceptance of technology is therefore the effect of positive and/or negative emotions related to the perceived, individually, level of simplicity of using a given solution and the needs that can be satisfied in this way (Wang et al., 2011). In this respect, the importance of the context in which wearables are implemented by consumers (activities they support) increases significantly, and decisions in this regard are preceded by an assessment of the features that these devices have and their price availability (Sachini et al., 2021). The profile of consumers is not without significance (the characteristics of a given group, including their lifestyle, their level of technological advancement or the nature of their needs) (Yang et al., 2016), because wearables must naturally fit into their everyday lives. This requires understanding the habits, attitudes and preferences of customers, including their acceptance of technology and involvement in the process of interacting with it. The characteristics that determine the propensity of customers to use wearables relate to specific categories of factors that translate into the level of satisfaction of using the device. This applies to physical features, including visual features of a given device (e.g. its size, colors, design, aesthetics, weight), functional features (ease of taking off and putting on, intuitive operation, multifunctionality, mobility, susceptibility to destruction), behavioral (range of possible interactions, including interpersonal, the level of generated experiences, evoked emotions), symbolic (brand, symbol of a given way of life, expression of the customer's identity), related to safety (does not lead to allergies, does not pose a threat to health in any way, provides protection against cyber-attacks) (Eservel et al., 2021; Chau et al., 2019; Nascimento et al., 2018). The context of the wearable's adoption is also important (Canhoto, Arp, 2017). They

accord with a complex space of moral and ethical rules, ways of communication, habits and their symbolism, fashion and aesthetics (Norene, 2016), which leads to an increased involvement in this type of interaction.

There are currently numerous models available that try to explain the issues of social acceptance of technology, such as: Theory of Reasoned Action (TRA), The Technology Acceptance Model (TAM Social Cognitive Theory (SCT), Theory of Planned Behavior (TPB) or The Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2). The analysis of the research conducted in this area shows that the TAM model is very popular, which may, however, insufficiently explain consumer behavior (Lin et al., 2007) and lead to simplifications. The process of the adoption of AI wearables, in this study, the UTAUT2 model was adopted due to its wide range of advantages. It is the model that is considered to have a higher explanatory power compared to other models of technology acceptance. It is comprehensive and based on a diversified scope variables and constructs. It allows both to effectively explain customer behavior while interacting with technology and to predict it (Gu et al., 2016; Venkatesh et al., 2012), which is important from the point of view of artificial intelligence solutions discussed in the study.

METHODS

Study Context

A literature review based on the full-text databases of Ebsco, Elsevier, Emerald, Web of Science, Scopus, Wiley shows an intense increase in the level of interest in the issue of wearables, starting from 2014, with the highest increase in publications recorded between 2014-2019. The analysis identified 50,476 publications on the subject of wearables (reviewed full-text publications; the phrase wearable is in the title, abstract, key words) in 2010 – 2021, of which publications in the Business, Management and Accounting category, which is the subject of the authors' further analysis, accounted for 443 publications. The largest number of studies in this area is conducted in the United States, India and China.

The analysis of the frequency of keywords related to wearables in the Business, Management and Accounting category and their quantitative analysis presented in the form of a "word cloud", where the frequency of occurrence was reflected in the size and thickness of the font (Figure 6), indicated that the key words are: wearable sensors (increase in the number of publications in the analyzed period = +433.3%), and wearable computer (increase in the number of publications in the analyzed period = +150.0%).

Figure 6. Keyword frequency analysis for wearables for the category: Business, Management and Accounting (2010 – 2021).
[Source: own study]

The analysis of the thematic areas of publications concerning the analyzed phrase in the Business, Management and Accounting category showed their dominant importance for Management of Technology and Innovation as well as Strategy and Management. At the same time, the analysis of the number of citations showed that the highest values of the Field-Weighted Citation Impact indicator are achieved for publications in the field of Industrial Relations (3.49), Tourism, Leisure and Hospitality Management (3.22) and Marketing (2.27). The review and assessment of issues raised in the most cited publications on wearable devices in the analyzed category indicates a dominant role of the issue of acceptance of wearable technologies in various market sectors:

- Gao Y., Li H., Luo Y., (2015). An empirical study of wearable technology acceptance in healthcare. *Industrial Management and Data Systems, 115(9)* - (cited by 259)
- Rauschnabel P.A., Ro Y.K., (2016). Augmented reality smart glasses: An investigation of technology acceptance drivers. *International Journal of Technology Marketing, 11(2)* - (cited by 140)
- Shin D.-H., (2017). Conceptualizing and measuring quality of experience of the internet of things: Exploring how quality is perceived by users. *Information and Management,54(8)* - (cited by 106)
- Tussyadiah I.P., Jung T.H., tom Dieck M.C., (2018). Embodiment of Wearable Augmented Reality Technology in Tourism Experiences. *Journal of Travel Research, 57(4)* - (cited by 98)
- Canhoto A.I., Arp S., (2017). Exploring the factors that support adoption and sustained use of health and fitness wearables. *Journal of Marketing Management, 33(1-2)* - (cited by 86)

It seems that despite the popularization of wearables and the related research on various contexts of their use (medicine, automotive, tourism, etc.), understanding of the broad spectrum of the process of their social acceptance is still limited. Comprehension of the impact of factors, such as the degree of innovation of wearables, their usefulness, as well as price value, availability, social influence and the acceptance or rejection in the group of end users is of key importance for marketing departments. Identification of the general social attitude towards wearables and the assessment of factors that may intensify or weaken this process requires further explication both at the level of the general framework of this acceptance, and at the detailed level, determined by the specificity of a given market sector. This knowledge is even more important in the case of solutions that are currently in the early stages of development, such as AI wearables, and which, according to analysts, may develop dynamically and undergo intensive commercialization in the coming years. This is important both for the stage of their further conceptualization, innovation, prototyping and the context of their future use, adaptation to the preferences and real needs of consumers with different levels of digital skills and technology-related experience. The conducted research helps to understand the essence of this process, which may be of importance for the further sustainable development of technologies to support people and constitute an element of their augmented intelligence. This justifies the decision made by the authors to conduct the preliminary research on AI wearable technology acceptance as a new area of human and AI related technology, in particular taking into account their marketing dimension.

Data Collection Instrument

The UTAUT2 model used by the authors was applied concerning, for example, mobile games, smartphone apps, internet banking, and e-learning systems. The analyzes conducted are based on the replication of original research (nuance of the studied dependencies, e.g. with regard to subsequent solutions based on digital technologies or their applications, taking into account different sectors or countries) or introduce variables to expand the scope of the research, in particular in the case of solutions commonly available on the market, e.g. various types of applications. The conducted research was preliminary, therefore, it was limited to replication research, considering that the obtained results will provide clues as to the variables with which the model should be enriched, as well as contribute to the implementation of experimental research based on real human and AI related technologies in AI wearables. The model used by the authors was adopted in accordance with the principles of cultural adaptation of measurement scales, ranking at the level of translation with the admission of modification where a literal translation was not possible and it was adapted to the specific context of the study

The study used a quantitative research approach (online survey), based on a structured research questionnaire. It consisted of 22 questions, divided into three parts. The first part includes questions about the respondents 'characteristics, the second part includes questions that allow to measure the construct, and the third part includes questions about the respondents' opinions about the possibilities and challenges resulting from the potential implementation of AI in wearables. Questions relating directly to the UTAUT2 model construct included a total of 28 items, each of which was measured using a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). It took about 20 minutes to complete the survey questionnaire.

A pilot study was conducted on a group of 20 respondents, which made it possible to eliminate potential ambiguities in the wording and repetitions. It was also confirmed that all items of the questionnaire had an appropriate level of confidence in internal consistency. After this validation process, the questionnaire was used in the proper research.

Due to the fact that the authors were aware of how the concept of artificial intelligence is perceived among people who are not related to technology, and shape their knowledge based on science fiction publications, games and information taken from the Internet, it was explained in detail before starting the research. The respondents were given the aim of the study, the essence of AI and its practical examples in the devices they use on a daily basis.

Development of Hypotheses

The emergence of artificial intelligence gradually, often unknowingly, changes the customer's life and surroundings. Subsequent products enriched with the possibilities resulting from this technology allow a consumer to go beyond the current cognitive and behavioral spheres. At the same time, however, the dissemination of this technology raises many concerns, which may hinder and slow down the acceptance process of AI wearables. For the purposes of preliminary research on determinants of the adoption of AI wearables, an assumption was made to transfer the hypotheses previously stated and confirmed in the literature in order to identify their effectiveness in the research on the newly developing AI wearables market. This will help define the general framework for social acceptance for these devices, with particular emphasis on the marketing perspective for their further commercialization. It was also assumed that the resulting empirical material would be used to modify and enrich the existing construct variables in further research on this issue.

Performance expectancy

Performance expectancy is defined as the degree to which consumers believe that using a given technology will help them achieve greater efficiency (benefit) in performing certain activities (Venkatesh et al., 2003). From this perspective, AI wearables can support consumers in monitoring their daily activities, analyzing their basic life parameters and decision-making processes. When consumers are convinced that these types of devices are useful in their lives, the greater the likelihood the devices will be accepted (Alalwan et al., 2017), which allows for the hypothesis that:

H1. Performance expectancy positively affects the behavioral intentions to adopt AI wearables

Effort expectancy

Effort expectancy is defined as the degree of ease associated with the process of using a given technology (Venkatesh et al., 2003). The majority of available studies (Dhiman et al.) in this regard indicate that the more consumers are convinced that the use of such devices is simple and intuitive, the more likely they are to use them. This means that effort expectancy may have a positive impact on consumer intention to use AI wearables, which leads to the following hypothesis:

H2. Effort expectancy positively affects the behavioral intentions to adopt AI wearables.

Social Influence

Social Influence is defined as the degree to which the consumer is convinced that people important in their life, such as family, friends, etc. (the social circle of an individual), believe that they should use a given technology and based solutions (Venkatesh et al., 2003). Social influence is particularly important in the initial period of acceptance of such solutions, where the reference group may, through sharing information, opinions and own experiences, determine the interest and willingness to use the devices (Alalwan et al., 2017), which allows for a hypothesis that:

H3. Social Influence positively affects the behavioral intentions to adopt AI wearables.

Facilitating conditions

Facilitating conditions are defined as the degree to which the consumer is convinced that the existing infrastructure, e.g. technological one, supports a given technology and devices based on it (Venkatesh et al., 2003). Their evaluation may either facilitate the approval process or slow it down and hinder it. Available studies show that consumers will be more likely to use a given technology if it is believed that there is support for its existence and further development (Alalwan et al., 2017). Therefore, it was hypothesized that:

H4. Facilitating conditions positively affects the behavioral intentions to adopt AI wearables.

Hedonic Motivation

Hedonic motivation is associated with enjoying the use of a given technology (Venkatesh et al., 2012). It seems natural that consumers will be more likely to reach for solutions that are found to be amusing, enjoyable to use or arouse joy and curiosity (Alalwan et al., 2017). AI wearables attributes can therefore become a manifestation of consumers' identity, which will positively affect the intention and decisions about their use. This allows the hypothesis that:

H5. Hedonic Motivation positively affects the behavioral intentions to adopt AI wearables

Price Value

Behavior in which potential users of a given technology compare, before making a purchase, the benefits they will obtain with the costs incurred for its purchase, seems justified. Price value becomes a compromise for the consumer between the expected benefits and the necessary costs. “The greater the price value, the higher would be the motivation to adopt the new technology” (Dhiman et al.2020) Therefore, the following hypothesis was put forward:

H6. Price Value positively affects the behavioral intentions to adopt AI wearables.

Habit

Habit is most often defined as the extent to which customers tend to perform behaviors automatically because of learning (Vankatesh et al., 2012), which leads to repeatability of their behavior, and is the result of their previous experiences. The past therefore determines the current decisions of customers and their behavior.

H7. Habit positively affects the behavioral intentions to adopt AI wearables

Sample

The study was based on a nationwide research conducted on a representative sample of 1,054 Internet users aged 18 and over in the period July-August 2021. 52.1% of the study participants were women, and 47.9% were men. The smallest number of respondents were under 25 (6.5%). The respondents aged 25-34 constituted 13.7% of the respondents, and those aged 35-44: 17.8%. Every fourth respondent was aged 45-54, and people aged 55-64 accounted for 16.9% of the respondents. The respondents over 65 years old constituted 19.1% of the respondents. Slightly more than 36% of the respondents had higher education, and 35.5% were people with secondary education. The respondents with primary and basic education accounted for 28.3% of the respondents. 38.1% of the respondents lived in small towns (villages and towns with less than 5,000 inhabitants), 14.7% of the respondents lived in cities with 5,001-30,000 inhabitants, and respectively: cities with 30,001-50,000 inhabitants (13.0%) and over 50,000 inhabitants (34.2%), of which every tenth respondent lived in the largest cities (over 500,000 inhabitants). The respondents assessed their financial situation most often as average, which was indicated by 59.7% of the respondents. Every fourth respondent assessed it as good, and 2% of respondents considered it very good. 11.3% saw it as bad, and 2.7% too bad. Almost 21% of the respondents were convinced of their high level of technological advancement, resulting from experience. 41.4% considered themselves to be moderately technologically advanced, but as many as 38% believed that they had little experience in this field, which, in their opinion, translates into a low level of technological advancement.

RESULTS

The Main Descriptive Analysis

Slightly over 11% of respondents encountered the concept of wearables for the first time three years ago, every fifth respondent had a chance to deal with it in the period of 1-3 years, and almost 41% had this contact in less than the last year. At the same time, however, 27.5% of respondents had never come across it before. 30% of respondents declared having and using this type of device, mainly smartwatches and fitness trackers. As expected, the age of the respondents happened to be a statistically significant variable. The willingness to buy this type of devices was the highest among respondents aged 25-34 (45% of respondents in this age group), and then it decreased with age. The existence of statistical relationships was also observed in the case of the level of technological advancement of the respondents, resulting from their experience. The higher it was in the opinion of the respondents, the more likely they were to purchase this type of equipment.

Respondents who had wearables were definitely satisfied with the devices, as indicated by almost 89% of respondents. Their experiences so far have been assessed positively, and the derived satisfaction can prove important in the case of making a decision concerning a purchase of a new version enriched with AI elements. The respondants appreciated, above all, the

functionality of their devices, their usefulness in everyday life, as well as the aesthetics and design. They considered the possibility of enriching wearables with solutions based on artificial intelligence as a natural market response to the needs of consumers. At the same time, the respondants indicated several areas of development of the existing functionalities of their wearables, in which, in their opinion, artificial intelligence could be of key importance: measuring daily activities (e.g. distance traveled) (77%), health diagnostics (74%), controlling smart home systems (72%), handling of phone calls and incoming notifications (71%). At the same time, among the biggest challenges related to AI wearables, respondents emphasized a significant increase in the risk of cyber threats aimed at obtaining data about individual users (64% of respondents), limiting their privacy (61%) and the potential unethical use of data collected by AI wearables (57%).

Measurement And Structural Model

The scales used were analyzed for reliability and validity via CFA.

Table 4. Fit indices of the measurement and structural models.

Fit Index	Measurement model	Structural model
RMR	0.065	0.066
CFI	0.933	0.931
GFI	0.832	0.830
NFI	0.891	0.890
IFI	0.933	0.932
TLI	0.921	0.920
PGFI	0.660	0.661
AGFI	0.788	0.787
RMSEA	0.067	0.067

The analysis showed that the value of the AGFI and NFI coefficients for the model are slightly below the threshold values.

Table 5. The Measurement Model.

Construct	Item	Loadings	CR	AVE
Expected performance	**PE1**	0.799	0.91353	0.725641
	PE2	0.877		
	PE3	0.877		
	PE4	0.852		
Effort expectancy	**EE1**	0.884	0.91576	0.731172
	EE2	0.822		
	EE3	0.87		
	EE4	0.843		
Social Influence	**SI1**	0.92	0.928117	0.811518
	SI2	0.877		
	SI3	0.905		
Facilitating conditions	**FC1**	0.447	0.793736	0.503319
	FC2	0.651		
	FC3	0.844		
	FC4	0.823		
Hedonic Motivation	**HM1**	0.536	0.812634	0.601526
	HM2	0.9		

	HM3	0.841		
	PV1	0.789	0,865652	0.68259
Price Value	**PV2**	0.861		
	PV3	0.827		
	HT1	0.799	0.816978	0.53191
Habit	**HT2**	0.614		
	HT3	0.639		
	HT4	0.839		
	BI1	0.828	0.902796	0.756075
Behavioral	**BI2**	0.879		
Intention	**BI3**	0.9		

Notes: PE-Expected performance, EE-Effort expectancy, SI-Social Influence, FC-Facilitating conditions, HM-Hedonic Motivation, PV- Price Value, HT-Habit, BI-Behavioral Intention, CR-composite reliability, AVE-average variance extracted
Source: own study

The reliability of the measurement was determined using the composite reliability CR (Fornell, Larcker, 1981). The acceptable minimum is 0.7, and the upper limit is 0.95 (Hair et al., 2013). Relevance was assessed in terms of convergent validity and discriminant validity. Convergent validity is usually assessed using average variance extracted AVE, the value of which for each latent variable in the model should exceed 0.5 (Fornell, Larcker, 1981).

Discriminant validity (Fornell, Larcker, 1981) for individual constructs of the research model and their mutual correlations are presented in the table below (all correlations are significant at the level of $p < 0.001$). The square roots of AVE were compared with the appropriate correlation coefficients, and their higher values indicate a positive discriminant validity test, therefore the individual latent variables differ significantly from each other. The reliability and validity of the measurements used for the proposed factor structure made it possible to create a multidimensional construct measuring the analyzed ratio against AI wearables.

Table 6. The Correlation Matrix and Square Root of the AVE.

	PE	**EE**	**SI**	**FC**	**HM**	**PV**	**HT**	**BI**
PE	0.851845							
EE	0.505	0.855086						
SI	0.573	0.284	0.900843					
FC	0.595	0.,706	0.404	0.70945				
HM	0.714	0.695	0.488	0.7012	0.775581			
PV	0.706	0.702	0.53	0.7042	0.7042	0.82619		
HT	0.701	0.498	0.581	0.618	0.677	0.712	0.729321	
BI	0.732	0.682	0.481	0.673	0.717	0.732	0.701	0.869526

Notes: PE-Expected performance, EE-Effort expectancy, SI-Social Influence, FC-Facilitating conditions, HM-Hedonic Motivation, PV- Price Value, HT-Habit, BI-Behavioral Intention

It is worth noting, however, that in the case of the FC construct and HM, PV and EE, these differences are very small, which may indicate that the FC construct is similar to them and therefore, the values of the AGFI and NFI coefficients for the model do not reach the threshold values (Tanaka, Huba, 1985).

The model presents relations between constructs, and the maximum likelihood method was used to estimate the model parameters. The model explains 81.4% of BI variability through changes in the estimated constructs.

Table 7. Structural Model Results.

Hypothesis	Beta	Error	t-value	p-value	Standardized Beta
H1: PE → BI	0.084	0.069	1.220	0.223	0.085
H2: EE → BI	**0.221**	**0.069**	**3.223**	**0.001**	**0.237**
H3: SI → BI	-0.028	0.031	-0.884	0.377	-0.042
H4: FC → BI	-0.120	0.124	-0.964	0.,335	-0.075
H5: HM → BI	**0.466**	**0.108**	**4.312**	*******	**0.367**
H6: PV → BI	-0.021	0.072	-0.290	0.771	-0.024
H7: HT → BI	**0.353**	**0.061**	**5.785**	*******	**0.466**

Notes: PE-Expected performance, EE- Effort expectancy, SI-Social Influence, FC-Facilitating conditions, HM-Hedonic Motivation, PV- Price Value, HT-Habit, BI-Behavioral Intention

In the model, statistically significant relationships indicate a positive effect of HT, HM and EE on BI. The Standardization Beta was used as the strength of the influence, showing that the strongest influence is HT, then HM and finally EE.

Age moderation did not change the significance of the HM, HT and EE variables, but it did affect the significance of FC, whose impact on BI is negative, and PE, whose impact is positive.

In the group of women, the influence of EE on BI ceases to be significant. Only the influence of HT and HM is significant, while among men the influence of HM on BI ceases to be significant. Only the influence of EE and HT remains significant.

Experimental moderation did not affect the significance of EE and HT. However, it caused the influence of PE to be significant and positive, and the influence of FC and PV to be significant but negative.

DISCUSSION

The main goal of this study was to identify factors influencing the acceptance process of AI wearables, with particular emphasis on the current research issues of human and AI related technology. To understand this, replication studies were conducted within the UTAUT2 model. In particular, it was possible to confirm the impact of effort expectancy, hedonic motivation and habit on behavioral intentions to adopt AI Wearables. This is important for the new way of perceiving the human and AI related technology, as well as for the future shaping of scientific-research and implementation paradigms related to it.

Table 8. Structural Model Results – Hypothesis.

Hypothesis	Path	Comments
H1. Performance Expectancy positively affects the behavioral intentions to adopt AI Wearables.	PE → BI	Not supported
H2. Effort Expectancy positively affects the behavioral intentions to adopt AI Wearables.	EE → BI	**Supported**
H3. Social Influence positively affects the behavioral intentions to adopt AI Wearables.	SI → BI	Not supported
H4. Facilitating Conditions positively affects the behavioral intentions to adopt AI Wearables	FC → BI	Not supported
H5. Hedonic Motivation positively affects the behavioral intentions to adopt AI Wearables.	HM → BI	**Supported**
H6. Price Value positively affects the behavioral intentions to adopt AI Wearables.	PV → BI	Not supported
H7. Habit positively affects the behavioral intentions to adopt AI Wearables.	HT → BI	**Supported**

The conducted research has confirmed that the habituation of consumers to the existing wearables solutions that they currently use is important for their future decisions regarding wearable devices enriched with elements of artificial intelligence. By using wearables, they have an established opinion about their current functionalities, they can assess their level of usefulness in their everyday life and identify those elements that could increase this level in the future. This seems to be fully justified, taking into account the fact that the general knowledge of consumers about a given technology has an impact on their level of perception of new solutions and the resulting acceptance behavior (Lin et al., 2007).

The research also indicated the importance of the enjoyment of using AI wearables, especially among women, who, as the previous research shows, are a group of consumers who are generally much more concerned about solutions based on new technologies, which was validated in earlier studies on the attitude to technology depending on by gender (Kim & Chiu, 2019). This may concern both the intuitiveness of use of these types of devices and the adaptation of the possibilities offered to actual expectations (Colgan et al.). This undoubtedly indicates a wide and varied area of factors that require further in-depth research and analysis, both in terms of their significance level and potential differences resulting from the variety of applications of available wearables, as well as the consumer profile.

The research also confirmed that the intention to adopt AI wearables is influenced by their perceived ease of use. Consumers expect this process to be as intuitive as possible. This applies to both direct interactions between the consumer and a given AI wearable device, especially at the beginning of the process, as well as the gradual acquisition of skills and proficiency in its use over time. Ease of use leads to a positive attitude of consumers, increasing their willingness to continue using this type of device (Chau et al., 2019). This raises the question to what extent are consumers of wearables prepared to popularize devices enriched with artificial intelligence and which elements associated with ease of use will be considered to be critical.

Also the results of the analysis of the influence of moderating variables: age, gender and experience on Behavioral Intention require further in-depth research, including, inter alia,

identification of situations in which the influence of these variables on individual variables of the construct could change (context).

LIMITATIONS

The publication is not free from cognitive, methodological and methodological limitations. However, it addresses new issues and the related new areas of their application, in line with the ongoing research on human and AI related technology. The conducted research has some limitations, which is a strong motivator for its further continuation and gradual deepening of knowledge in this field. This applies to both the research methods used (it would be advisable to include qualitative methods, including in particular the ethnographic ones) and the scope of the research conducted (broadening the spectrum of consumer behavior affected by AI wearables). Moreover, as mentioned earlier, the FC construct is similar to HM, PV and EE, which means that the value of the AGFI and GFI coefficients for the model does not reach the threshold values.

CONCLUSIONS

Digital technologies have now become a catalyst for subsequent stages of evolution, aimed at transforming the existing paradigms and solutions based on them. The literature review confirmed that these technologies have created a wide range of fascinating and previously unavailable possibilities. Artificial intelligence, as an element of customer support, is undoubtedly an exciting area of new interaction between human beings and technology, inextricably connecting with each other in a network of mutual digital connections and dependencies. However, many possibilities remain unknown, which results from their great diversity, complexity and the enormous dynamics of the technological changes taking place.

The AI wearables market is definitely at an early stage of development, leading to the gradual formation of augmented intelligence of the customer, and the process of social acceptance of these types of solutions requires much more than just a passing fascination. The shaping of conditions conducive to the acceptance of technologically advanced solutions must be based on understanding their essence and the nature of the human and AI relations, while being aware of the resulting challenges and limitations. It seems that the issues discussed in the study constitute a space for new research, including interdisciplinary and multicultural research, as well as may affect the processes of designing and testing AI wearable devices, accelerating the process of their commercialization and popularization.

IMPLICATIONS FOR RESEARCH, APPLICATION OR POLICY

Research Implications

The development of artificial intelligence and its implementation possibilities in every sphere of consumers' lives significantly increases the potential expectations towards it. This means the

need to identify the way in which a human interacts with devices based on this technology and to determine the factors determining its acceptance. The conducted research is an extension of the current authors' research and fits into the international discourse on the role of human and AI related technology, including in marketing. The analysis of the level of social acceptance of AI wearables based on the UTAUT2 model is in part a replication of existing global research in this field. The results obtained form the basis for further analysis of the determinants of social acceptance of technology, especially in relation to new constructs related to an increasing spectrum of consumer behavior as a result of their interaction with the technology, as mentioned in the Discussion section. There should be a focus on the conceptualization and systematic deepening of the impact of potential factors. It would be advisable to look for relationships that take into account the cultural differences of customers, which would allow for the possibility to find potential regularities and cause-effect relationships in the context of AI wearables acceptance.

Practical Implications

The market success of AI wearables depends on the level of acceptance of these types of solutions by consumers. The conducted research provides information that can support both the creators of wearables and employees of marketing departments. This applies to the design of AI wearables functionalities important for consumers, taking into account the expectations as to the technical parameters and quality of these types of devices, affecting their expected performance and ease of use. The recommendations resulting from the study are important from the point of view of designing functionalities of AI wearables that are significant for consumers, taking into account the expectations as to the technical parameters and quality of these types of devices. The research results can also provide guidelines for the optimization of marketing communication strategies implemented in this area, in order to be more effective, referring to the real consumer needs and expectations, while contributing to minimizing the significance of the concerns raised.

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