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From the Editors-in-Chief

HOW ARTIFICIAL INTELLIGENCE AFFECTS EDUCATION?

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Abstract: *Acquiring specific knowledge that can be tested by means of a test is a very common scenario present in the education system, which determines the passing of successive levels of education. The simultaneous development of technology, in particular artificial intelligence models available through publicized large language models, makes this scheme vulnerable to abuse and pitfalls. Updating knowledge and awareness of the advantages and risks of the use of artificial intelligence in education (AIED) is the responsibility of the research community and global policy. This text is a voice that attempts to redress the balance between the enthusiasm for the use of AI in education and the dangers that come with it. Public awareness develops more slowly in this case than the technology itself, and the regulations created are no substitute for ethics and decency, at the initial stage of their introduction, before certain patterns and rules have become established.*

Keywords: *artificial intelligence, education, AIED, human-technology.*

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AIED socio-technological background

The rapid development of artificial intelligence (AI) tools and techniques has been the cause of vigorous debate in recent times. Headlines on the one hand report that AI will be depriving people of jobs while other headlines promise that thanks to artificial intelligence we will no longer have to work. Whether and how the development of artificial intelligence will affect the process of education (AIED – Artificial Intelligence in Education) and skill acquisition is still under consideration. While one gets the impression that the revolution has already begun, as academic articles cite numerous examples of AI-based learning platforms (Cukrova et al., 2023) or student text assessment tools (Cochran et al., 2023) the public does not seem to control either the direction or pace of change.

New technologies are indirectly revolutionizing the teaching system. Scholars and students are eager to use large language models to acquire information or edit texts through publicly available generative tools, like exemplary ChatGPT, which they unreflectively share with teachers. Teachers who focus on non-interactive checking of student-delivered content are checking the results of artificial intelligence, not their protegees. Meanwhile, CEO of OpenAI, Sam Altman, described ChatGPT as "incredibly limited, but good enough at some things to create a misleading impression of greatness. It's a mistake to be relying on it for anything important right now. It's a preview of progress; we have lots of work to do on robustness and truthfulness." (Tweet on December 11, 2022).

This is particularly painful in those countries where centralized education does not focus on critical and analytical thinking, does not stimulate entrepreneurship, innovation and creativity, and does not teach teamwork and empathy (e.g., the Prussian model, which has persisted in some European countries). At the same time, teachers' dubious authority leads them to act in a schematic and uninvolved manner, based on reproductive verification of knowledge.

Thus, since AI is not reliable enough and has no so-called "moral compass" in itself, the very idea of using AI should be ethical. We should monitor and supervise the use of AI, so as to teach people to use modern technologies in this way. We should take care that the context and manner of AI use and the result of the action does not violate our/society's "moral spine."

In anticipation of the regulations that various countries around the world are working on, including the European Union (EU AI Act), we should make teachers rethink the way they assess students and raise awareness of technological advances among teachers themselves. Extant literature has demonstrated that teachers have limited capacity and skills to engage in high quality assessment practices that move learning forward, but they may have to change how assessment is currently done to more innovative assessments. The present voice is therefore an appeal to supplement the discussion affirming the use of various elements of AI in education with skeptical voices addressing the risks and dangers.

Perspectives and examples

According to numerous literature studies, artificial intelligence has great potential for use in several areas of education. The first potential noted lies in the personalization of education. This is because few teachers are able to adapt to the requirements and expectations of individual students in the classroom. Another benefit lies in the tutoring capabilities through which AI systems are able to adapt to individual students' learning styles and individual knowledge levels. AI systems can also be used for grading. They can do this according to an accepted key, but can evaluate more abstract papers such as essays. Modern chatbots can also be an excellent source of feedback on courses taught. Evaluating student responses allows gaps in the learning process and the course itself to be identified and necessary improvements to be made. Chat communication also allows pupils and students to verify their own knowledge in a more anonymous and direct way. Verifying one's own mistakes is an essential part of the process.

Contemporary literature reports many practical examples of the use of AI in learning (Beck et al. 1996, Chen et al. 2020, Zhang et al. 2021). Examples can be found in several branches of AIED systems. Among others these are student-centered systems and teacher-dedicated systems (Holmes 2022).

Among the historically most popular solutions dedicated to students are Intelligent Tutoring Systems (ITS), which aim to provide automated, tailored instructions (Polya 1945, Domisco 2023). Students can use AI-assisted apps to learn languages (SayHi 2023) or learn mathematics (Photomath 2023). With AI-assisted simulations, they can learn chemistry (Behmke 2018), write an essay (GPT-3 2020) or, as in the case of IBM Whatson, hold a discussion (Hussain 2017). A very interesting functionality of the Automatic Formative Assessment is provided by the Grammarly environment (Grammarly 2023).

From an educators' point of view, in addition to dedicated interfaces for monitoring student progress in ITS-type systems, quite functional applications of AI are plagiarism detection (Turnitin 2023), validation and selection of teaching materials (X5GON 2023, Clever Owl 2023) and tools for Automatic Summative Assessment (Ramesh 2021, ETS 2023).

It is impossible to list all the examples of the use of AI in education, but it can be firmly admitted that we are not still discovering new layers of possibilities that artificial intelligence brings to education.

A skeptical outlook

A sound analysis of the impact of artificial intelligence on education should also take consider skeptical voices alarming about possible dangers. It should be noted that relatively few voices touch on the risks and drawbacks of introducing AI systems into education.

One aspect that is often overlooked is cost. In addition to the sheer cost of creating LLMs, access to them is increasingly monetized and thus becomes available only to the more wealthy. In some cases, there are extreme situations where teachers cannot afford access to AI technology while students are freely using it. Another issue is the addiction to technology, which, through its use in everyday tasks, results in the disappearance of the natural ability to overcome challenges among its users. This, in turn, raises the black vision of the irretrievable loss of knowledge/skills when the AI system needs to be fixed (temporarily) or simply ceases to exist. Another casualty of the widespread use of AI technology is the weakening of interpersonal relationships. The average person, especially one who is addicted to modern technology, is unable to build relationships with other people properly. Contact with another person becomes less attractive than interacting with a seamlessly adaptable digital environment.

It is also worth noting the immanent characteristics of artificial intelligence systems are habitually characterized by bias caused by unbalanced learning data. As an example, some studies profile LLMs against political preferences (Santurkar et al. 2023, Tornberg 2023). AI systems condition their actions on context, which, imprecisely expressed, can suggest unsatisfactory or even wrong solutions. Another noteworthy feature of systems is their tendency to build their power on patterns, which may stand in opposition to creativity and innovation.

The use of AI in education, especially at the stage of enthusiasm around emerging technology, can lead to the teaching profession being depreciated as uncompetitive with AI tools. This is overlaid by the widespread belief that AI will put many people out of work. All of this, however, ignores the invaluable role of humans in understanding the subject matter being studied and in the selection of materials, which we know modern tools select moderately effectively. The elimination of the humans from the learning process can result in reduced effectiveness in making critical decisions in new situations. In such a context, intuition, which is developed in classrooms based on discussion and inference, is often useful.

An in-depth analysis of the advantages, of which there are more, and the risks, of using AI leads us to reflect that a balance is needed between the use of technologies that make our lives easier and the people who use these benefits. The aim of using AI is not to replace educators but to make their job easier. AI tools can be integrated into the digital classroom environment, where students can contextually benefit from different forms of communication, consultation and knowledge acquisition. At the same time, the technological awareness of teachers needs to be worked on very hard so that they can develop useful solutions in the educational process together with their students.

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EXPLORING RELATIONSHIP EXPECTATIONS AND COMMUNICATION MOTIVES IN THE USE OF THE DATING APP TINDER

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Abstract: *Tinder is one of the most popular dating apps for heterosexual people/people seeking partners different from their own sex. In consequence, Tinder for some analysts the app has a reputation of being a hook-up app, albeit for other scholars, the app is simply a mediated venue for romantic acquaintanceship. In order to contribute on the discussion of the competing debate about Tinder and online dating in general, this study surveyed 278 participants regarding their Tinder usage, relationship expectations, and communication motives for using Tinder. Current Tinder users reported less intent to marry and more negative attitudes about marriage. Findings also revealed that men and women use the Tinder differently in terms of their communication motives. Specifically, men are more likely than women to use Tinder for the motives of affection, control, and escape. Older adults report using the Tinder significantly more for the motive of pleasure compared to college aged adults.*

Keywords: *Tinder, romantic relationships, communication motives, relationship expectations.*

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INTRODUCTION

The presence of computer–mediated communication technologies (CMC) has become ubiquitous (Hancock et al., 2020); for example, the population from 8 to 18 years old is 10.45 hours daily (Rideout, et al., 2010). Along to this technological canvas, the adoption of smartphone technology got widespread: there are more than 2500 models of smartphones, 2 million apps, and 7 billion of users; considering that the world population is around 6.8 billion, this means that there is almost one smartphone for every individual in the world (Sun et al., 2022). Thus, derived from this widespread technological adoption, one conclusion can be certainly drawn: the boundaries between 'mass' and 'personal' communication scholarship are no longer tenable (Pfau et al., 2008; Perloff, 2013), because the formation of the fundamental interpersonal relationships is highly mediated through technology; indeed, one in five marriages is currently sparked online (Sprecher et al., 2014); and, not surprisingly, in 2012, a new online dating app exclusively available for iOS and Android smartphones devices took over the cyberdating market: Tinder. It is important to note that Tinder is not the only online dating app exclusive to phones (Bertoni, 2014a), there are other apps such as Grindr and Match and eharmony online.

Tinder is one of the most popular apps among heterosexual people between 18 to 30 years old (Bertoni, 2014a; Swann, 2015; Sumter, et al., 2017, Wagner et al., 2022); 30 million people used Tinder, which is estimated to make more than 15 million matches daily (i.e., 14 matches per second) among about 1.2 billion profiles (Bertoni, 2014b). The rapid stampede of cyberdating in general results from a combination of online dating matching–software, pervasive access to personal computers, GPS Technology, and its massive dissemination through social networks diffusion effects and mass media advertisement and was originally linked to Facebook profiles (Finkel, et. al., 2012), which was also exponentially enhanced with the actual adoption of smartphone technology (Cecere, et al., 2015). People are attracted to the gamification of Tinder because it is about matching with potential mates and you can swipe on profiles that you are interested or not interested in (Cecere et al., 2015). In consequence, Tinder is in the eye of academic and popular storm: for some analysts the apps has a reputation of being a hook-up app (Hoffman, 2015) because it promotes virtual affairs; whereas for others scholars: "Tinder should not be seen as merely a fun, hook up without any strings attached, but as a new way for emerging adults to initiate committed romantic relationships" (Sumter, et al., 2017, p. 67). However, before understanding media effects or deciding that this app is just a venue for romantic initiation, the characteristics of audience involvement such as motivation and selectivity should be addressed at first place (Rubin, 2009). In fact, individuals are making 'actual' romantic decisions in the online dating context (Sprecher, 2014), and then virtual contexts can be applied to face-to-face communication contexts (Lister, et al., 2009); for example in political communication scholarship, Bennet & Iyengar (2008) suggest the importance of recognition of individuals' subjective aspects of individuals while engaged in the CMC consumption in order to extend the understanding of experimental findings linked to actual communication conditions. Therefore, here is the relevance for this study to analyze users' expectations and motives to further the comprehension on Tinder to foresee any potential risk of future media dependency, because when needs and motives instigate narrow information–seeking strategies while using a given media outlet this generates dependency, which also “leads to other attitudinal or behavioral effects and feeds back to alter other relationships in the society” (Rubin, 2009, p. 182).

To our knowledge, research on this Tinder and other new dating apps has primarily focused more on general users’ motivations to explain what individuals do with this app such as socialization, self–boost, infidelity, and so on, then the next important scholarly step is to analyze the particular expectations and motives associated specifically to romantic outcomes (Niehuis, et al., 2020; Weiser et al., 2018). The analysis of expectations and motives is paramount for media effects research because it explains why users choose a given media (Nabi, 2009). Therefore, being modest in its exploratory and descriptive scope, the purpose of the present study is to explore users’ relational expectations and communication motives in Tinder specifically.

While previous online dating sites and apps that ask users to create in-depth personal profiles, Tinder innovates online dating by providing users a seemingly endless selection of photos of potential mates without the need to answer questionnaires or forms (Bertoni, 2014a). It is inferred that the algorithm of the app links users’ contacts from Facebook profiles to provide photographs of potential romantic candidates. After solely looking at photos of potential mates, users swipe right if they like a person and left if they do not (Bertoni, 2014b). If both parties like each other, the platform provides a parallel interface to send messages to one another to decide whether to meet in person and exchange personal contact information.

In an attempt to understand why users, immerse in Tinder, Sumter et al. (2017) conducted a study to analyze users’ motivations. Findings suggest that a) ‘love’ motivation was stronger than ‘casual sex’ motivation, b) males users showed a higher motivation for casual sex than females, c) users engage through Tinder because of the ease of communication through this app where men feel to be more benefited, d) in terms of self–validation there were no significant differences between genders, and e) users also immersed themselves in Tinder because of the thrill of excitement were those individuals with higher levels of sensation seeking use it more. This study concludes that “Tinder goes beyond the hook up culture” (p. 74). This asseveration contests Finkel and colleagues (2012) argument about online dating as an unable CMC platform to guarantee successful romantic partnering since: first, online dating algorithms are based on criteria of psychological similarity, compatibility, or a combination of both, but there is no substantial empirical evidence to suggest that homophily assure successful romantic outcomes; additionally, since these algorithms are proprietary of dating companies and they do not release for academic examination, online dating services cannot be subject of further scholarly examination (Finkel, et. al., 2012). Therefore, it seems too early for the present study to make such claim, and scholarly work needs to dig more in individuals’ intentions encompassed in relationships expectations and communication motives to avoid conclusions that end up supporting online dating business rather than extending theory.

LITERATURE REVIEW

Online dating is a new technological advancement to facilitate romantic initiation (Finkel, et al., 2012). Finkel et. al. (2012) delineate online dating functioning on the basis of its three main features: 1) access to a vast number of profiles of which gives users a false perception of having more chances to succeed ; 2) a convenient and discrete communication channel to initiate contact; and 3) a romantic compatibility–matching algorithm to pair potential romantic candidates. Moreover, Quiroz (2013) suggests that these online dating features were substantially enhanced by merging with the fast development of hand-held devices and satellite app technology transforming online dating into "location-based dating" (Quiroz, 2013). As a result, online dating's popularity burgeoning is often explained through the massive effects of social networks and increased access to technology which both were not available during previous computer-dating or video dating (Finkel et. al., 2012). The smartphone innovation with GPS technology made cyberdating very appealing.

Notwithstanding, this innovation is not 'simply' an advancement of hardware modality; indeed, the type of CMC device or platform has a forceful impact on users' perceptions of the interactivity experience. Xie and Newhagen (2014) compared the effects of interface proximity in three media platforms (i.e., desktop, laptop, and hand–held devices) while participants received university emergency alerts. Findings suggest that hand–held devices (i.e., IPads and smartphones) significantly enhance more the feelings associated with this alerts (i.e., anxiety in this specific study) compared to the other type of devices; thus, it was shown that interface proximity moderates users' perceptions of the interactivity experience in a given mediated task. On top of this idea, it can be inferred that Tinder enhances the online dating experience more than others apps because of its particular exclusivity for smartphone technology; thus, the distance between users and the dating event is minimal. Certainly, it will not be surprising to infer that the decision of Tinder (as a Company) of choosing the smartphone technology as its sole platform was purposely to intensify the online dating experience.

Although Tinder is particularly well–suited for smartphones that allows users to quickly look at pictures, most previous and others cyberdating platforms are similarly structured (Rosen, et al., 2008; Finkel, et. al., 2012; Sprecher, 2014): users post a photograph and provide personal information and other relevant demographic information about themselves. Tantamount to the typical combination of visual and textual information of users as the main structure of online dating software configuration, the most used theoretical framework for research on this subject has been the Hyperpersonal model: "the hyperpersonal CMC model (Walther, 1996) posits that CMC users take advantage of the interface and channel characteristics that CMC offers in a dynamic fashion in order to enhance their relational outcomes." (Walther, 2007, p. 2540). Affordances refers to the properties of the perceived environment that provide possibilities for actions, and this concept is primordial for CMC use because the design of a given technological product should respond to the question about how that product can make users to 'afford' a given experience (Pucillo, & Cascini, 2014). For the particular case of online dating, such CMC affordances are described by Walther (1996, 2007) as it follows: a) editability lined up with malleability to transmit messages, b) unlimited time to construct and edit those messages thereafter, and c) physical isolation from receiver. Therefore, these medium characteristics allow users to hide any nonverbal and verbal cues that may jeopardize relationship goals where users execute control on visual and textual information while interacting. In consequence, the overall CMC affordances instigate users to reallocate cognitive resources to message composition (Walther, 2007) for managing impression behavior where, in addition to this, the physical isolation prompts anonymity and makes users experience more disinhibition while interacting (Walther, 2007). In other words, "[…] social evaluations […] are not impeded by messy hair, lack of makeup, or normal imperfections" (Walther, 1996, p. 20, Italics added), then it is more appealing for individuals to use this technologies for first impression formations.

As a direct denouement of the suitability of this model for online dating, research findings yield results on users' self–presentation and self–disclosure communication strategies in CMC interactions (e.g., Gibbs, et al., 2011; Rosen, et. al., 2008). Indeed, Segrin and Flora (2011) reported that much of the research has focused on how impressions are managed online, especially with regard to self-disclosure, and how people vary in their use and dependence on technology for dating. Perhaps because of the high stakes involved in creating a positive impression, roughly one third of photos on online dating profiles are rated by independent judges as "not accurate" (Hancock & Toma, 2009). Women's photos are less accurate than males, either because the photo shows them at a younger age or because it has been retouched in some way. Nonetheless, in one hand, physical attractiveness is one of the features most unclear in online dating profiles; albeit, in the other hand, it is rated as the most important aspect in online dating than the traditional 'old–fashioned' FtF dating (Rosen, et al., 2008).

Other online dating forums rely heavily on written profiles that are often a mix of reality and an ideal presentation of oneself (Yurchisin, et al., 2005), and these forums have not become as popular as Tinder did in terms of number of users and the rapidness in which it got that popular. On the other hand, Tinder differs from other online forms by encouraging less self-disclosure before any FtF contact. Ramirez et al. (2015) investigated the association between the amount of time spent online before meeting the potential candidate in real life and motivation to meet the person FtF. Although their investigation did not include analysis of Tinder usage, they found that the more time daters spent on the online platform, the less motivation they had to meet the other person face-to-face because it dampened the perceptions of closeness.

While using Tinder, users primarily swipe pictures, and this mechanic for use rules out momentarily the textual element from the online dating experience. This is crucially important, because the way in which users communicate with others online daters is contingent upon the way the site is set up (Whitty, 2008); in other words, interface design and boundaries plays the leading role on individuals' communication behavior in CMC settings. Secondly, it seems that as more an online dating interface emulates the naturalness of users' experience of first impression formation in FTF settings, the more it gets popular.

Nonverbal Research on interpersonal relationships formation indicates that physical attractiveness is what actually motivates individuals for initial approach at large (Richmond, et al., 2007), and even more for romantic initiation: the level of physical attractiveness is a better predictor for initial encounters than psychological traits (Tidwell, et al., 2012). Not surprisingly, the same pattern is present in online dating, but even in a more pronounced fashion: Whitty (2008) conducted a qualitative study to understand how individuals present themselves on an online dating site, as well as their judgments on how others present themselves on this site. Sixty online daters (e.g. 30 men and 30 women) were interviewed for this research; the findings suggested that participants consistently believed on a supreme importance of posting an outstanding personal picture over any other personal characteristic. Then, she found that what really triggers contact initiation in cyberdating is individuals' attractiveness with no significant differences between genders, and this is surprising nonetheless, because physical attractiveness has been found to be a larger predictor to make the decision for contact initiation more for men than women (Deyo, et. al., 2011).

Therefore, in a given online dating setting in which the visual aspect is the most salient aspect where the space for negotiation of textual meanings is reduced to its minimal condition possible such as Tinder, then the analysis of users' expectations and motives becomes more critical because: first, the selection and use of a given media, and the communication behavior displayed in CMC context is a goal–directed, purposive, and motivated task (Rubin, 2009), and only these elements are at hand; on top of this idea, the reduced amount of textual information does not give enough space to apply the Hyperpersonal model to understand users' communication strategies, but expectation and motives instead. Additionally, structural differences or the way in which information can be accessed and sent it play an important role on users' communication behavior as Whitty (2008) suggested earlier.

The analysis of Tinder on this matter is important due to its specific differences in software configuration (i.e., swiping faces) and platform exclusivity (i.e., smartphone) compared to other online dating services. To conclude this section, Tinder is noted for prompting quick progression to face-to-face interaction. Tinder avoids in-depth written profiles; photos appear to be especially crucial. Tinder's interface architecture and its modus operandi perhaps suits better to human perception of forming impressions based on physical appearance assessment (Arias & Punyanunt–Carter, 2016). And, being emotions the driving force for humans to adapt to situational conditions that are externalized as intentions; thus, an examination of the relationship expectations and communication motives along with the communication nature of online dating is paramount.

CMC Impact on Expectations And Motives

The analysis of relationship expectations and communication goes beyond its descriptive nature. Pucillo and Cascini (2013) explain that the design of interactive devices should address users' experiences, and the experimental outcome takes place at the moment of using it and in the context of interaction; in consequence, artifacts design must consider users' personal goals, expectations and emotional aspects along user's agency while interacting with technology (Pucillo & Cascini, 2013). Therefore, as an inversed engineering process, it is worth analyzing specifics users' expectations and goals to understand any technological innovation either for design or use.

In fact, scholars have emphasized over and over the role of anticipation in online dating as its intrinsic nature (Gibbs, et al., 2006; Rosen, et. al., 2008; Sprecher, 2014). Additionally, Finkel and colleagues (2012) indicate that "[…] Rather than meeting potential partners and then slowly learning various facts about them, users of online dating sites typically learn a broad range of facts about potential partners (and vice versa) before deciding whether a first meeting is desirable" (Finkel, et. al. 2012, p. 19, italics added). Thus, this suggests that users have more time for planning to manage their impressions for romantic initiation. Subsequently, if any media evoke a wide range of emotions which prompt users to select a given media (Nabi, 2009), then individuals may focus firstly on their expectations and communication motives before choosing Tinder or any other online dating venue.

Relationship Expectations

Although the average age of first marriage is climbing, young adults are not delaying participation in romantic relationships (Thornton & Young- DeMarco, 2001). In part, this has led to a changing architecture of premarital relationships and less stigma associated with short-term dating. People now spend more time than ever before in romantic relationships outside of marriage (Sassler, 2016). Moreover, the relationship patterns of those who marry in their early 20s are different from those who delay marriage (Sassler, 2016). Those who delay marriage tend to have more premarital relationships, are more likely to cohabit in those relationships, have more liberal sexual attitudes, and engage in more risky behaviors in those relationships (e.g., binge drinking, use of illegal drugs) (Carroll et al., 2007; Uecker, 2008). College graduates, for example, are a group who tends to delay marriage in pursuit of education, career, and financial goals, yet they go on to marry at a higher rate than less educated or lower income counterparts; thus, the social and economic context in which these individuals make romantic decisions influence their expectations. Notwithstanding, it is not clear to what extent online dating reflects this generational shift, or, it is an outcome from CMC adoption.

The romantic outcome dependency theory posits that one's behavior is affected by the context and others' behavior in the same context, and romantic expectations and motives are not simply representing individuals' goals, by contrary it reflect relational patterns in terms of actual outcomes. Given that Tinder appears to be a platform for quickly meeting a large number of available candidates to fulfill short-term relational goals, the intentions and motives may need to match with these desired outcomes, and then the question is: do Tinder users, who may be well-educated young adults delaying marriage, have different relational expectations and motives in those premarital relationships? Tinder has carved a unique market niche that facilitates simply the meeting-up of people who presumably have less intent to marry at present. The structure of Tinder, which provides little information about potential users aside from physical appearance, perhaps is compatible with short-term sexual selection strategies that are more focused on physical appearance as opposed to long-term sexual selection strategies that predict people will assess partners on other more in-depth qualities (Buss & Schmidt, 1993).

Before the advent of Tinder, Stephure et al. (2009) explored the idea that age, or the perception of having limited time left, might change people's involvement in online dating. In doing so, they uniquely applied Socioemotional Selectivity Theory (Carstensen, 1993, 1995), which suggests that time changes people's perspectives and social goals. Carstensen proposes that life stage changes one's perspective with regard to goals for information seeking, self-concept development, and emotional comfort and gratification. In theory, social goals focused on self-concept and information-seeking peak in adolescence and young adulthood. Self-concept motives prompt people to interact with a variety of people to get feedback about oneself, by comparing oneself to others, seeking feedback about how one is viewed, and by monitoring views about oneself. Information-seeking motives prompt people to experience and learn about the world. Through interactions with people, even novel and unfamiliar people, who help gain information about what other people and the world are like. Indeed, gaining information and making numerous social connections might prove to be helpful in years ahead as young adults develop careers and future opportunities. In short, self-concept and information seeking goals tend to be focused on self-development with an eye toward the future; and, again the goal of emotion regulation is focused on surrounding oneself with emotionally meaningful relationships that are high in emotional intimacy.

This is a very present-oriented goal for people, and one that becomes especially important when people perceive that time is running out, and this feeling is more enhanced when the CMC platform makes the experience so close between the user and the dating event (see Xie & Newhagen, 2014). With limited time left in life and the impression of being there endured by technological innovation of the app, there is more urgency to focus on seeking a lot of new, exciting, and expanding relationships rather than the meaningful relationships that matter most. Also, one's self-concept is likely already stabilized later in life. On the other hand, Stephure et al. (2009) hypothesized that involvement in online dating increases with age, presumably because as people get older and perceive that they have limited time left to meet a life partner, they are more likely to turn to online dating as a means of more quickly finding an emotionally meaningful romantic relationship, but Tinder is among young adults. Contrary to Stephure et al. (2009), it is argued that only a certain type of involvement in online dating (such as *eHarmony, Match, Perfect Match*) increases with age because of how the information is structured differently compared to Tinder. As people age, they may be increasingly interested in online sites that help them meet an emotionally meaningful long-term partner, then more textual information is needed to achieve this goal.

However, Tinder appears more geared toward finding lots of short-term dates may be more appealing to young adults, or any adult with less intent to marry at present. In this research, Tinder users' intentions to marry and attitudes toward marriage as a means of exploring whether Tinder is used most for short-term date selection rather than long-term mate selection was assessed. Considering their age, most young adult Tinder users should theoretically be at the peak of the self-concept and information seeking social goals of Socioemotional Selectivity Theory. Thus, some Tinder users may attempt to affirm their self-concept needs and seek a wide variety of new experiences, especially if they felt they had plenty of time to find a more emotionally intimate, longer-term marital relationship or if they have negative attitudes about the possibilities of doing so.

RQ1: Do current and non-current Tinder users differ with regard to relational expectations, in the form of (a) intent to marry and (b) attitudes toward marriage?

Communication Motives

What are the reasons why young people communicate via Tinder? Or what are the reasons to communicate through Tinder rather than other online dating venues? According to Rubin, et al. (1988), people generally communicate to either gain control or compliance, to relax or to avoid other activities, to express emotion, to express love, and to share enjoyment. Communication motives affect what, how, and who individuals talk to (Graham, et al., 1993); in other words, communication motives are reasons which reflect why people communicate with each other, and it is possible perhaps individuals have specific communication motives when using Tinder.

Older individuals tend to communicate more for affection, whereas younger individuals do so more for pleasure, escape, control and inclusion. Women tend to communicate more for relaxation, inclusion, affection, and pleasure than men (Rubin et al., 1988). Given that Tinder users are likely younger, it is expected that people communicate primarily for pleasure, escape, control, and inclusion. It is also expected that women more so than men to communicate for relaxation, inclusion, affection, and pleasure.

RQ2: Is there a difference between males and females and their reported Tinder communication motives?

RQ3: Is there a difference among age groups and Tinder communication motives?

METHODS

Sample

Research participants were 287 college students from a variety of majors enrolled in an introductory communication course at large public southwestern university in America. Participants ranged in age from 18 to 32 years old (M = 20.88, SD = 1.78). The sample consisted of 83 males (28.9%) and 204 (71%) females. In terms of sexual orientation, 6 (2.1%) said they were gay, 2 (.7%) said lesbian, 273 (93.4%) were heterosexual, and 7 (2.4%) bisexual. The ethnic or racial background of the participants included: 194 (67.6%) white, 1 (.3%) Native American, 28 (9.8%) Black, 1 (.3%) Pacific Islander, 4 (1.4%) Asian, 49 (17.1% Hispanic/Latino, and 9 (3.1%) other/multi-ethnic. A majority of the participants stated that have used Tinder in the past: 260 (90.6%) said yes and 27 (9.4%) said no. In terms of political affiliation, 67 (23.6%) were Democrat, 157 (54.7%) were Republican, 47 (16.4%) were Independent, 13 (4.5%) were classified as "other." In terms of frequency in the past 30 days, 114 (39.7%) said that they never used it, 39 (13.6%) said once, 74 (25.8%) said a few times, 20 (7.0%) said weekly, 13 (4.5%) said daily. When asked about how much time they spend when they use/view Tinder, 36 (12.5%) said 1 minute, 170 (59.2%) said 10 minutes, 43 (15%) said 30 minutes, 7 (2.4%) said about 45 minutes, and 4 (1.4%) said about 60 minutes. In terms of relationship status, 147 (51.2) were currently not in a relationship, 108 (37.6%) stated that they were dating one person, 18 (6.3%) said they were dating multiple people, 9 (3.1%) were cohabitating with a relational partner, 2 (.7%) were engaged to marry and 2 (.7%) were married.

Procedures

Once the study was approved by the Human Subjects Review Board, the following procedures were used in the data collection process. Two hundred and eighty-seven college-aged participants enrolled in the basic communication course were asked to complete the survey if they used Tinder or are current users of Tinder. Participants were told that their responses would be kept confidential and anonymous. Students who participated were offered course research credit. Students who did not choose to participate were given other opportunities to obtain their required research credit.

Instruments

Marital Attitudes and Intentions

Marital attitudes were assessed using Park and Rosen's (2013) 10-item General Attitudes Toward Marriage Scale. The Likert-type items range from 0 (strongly disagree) to 6 (strongly agree), with higher scores representing more positive attitudes toward marriage. Sample items include, "I intend to get married someday," "I have doubts about marriage" (reverse scored), and "Most marriages are unhappy situations" (reverse scored). Cronbach's α was .84.

Marital intent was measured using Park and Rosen's (2013) 3 –item Intent to Marry Scale, which allows intent to marry to be evaluated as a construct separate from positive or negative attitudes toward marriage. The Likert-type items range from 0 (strongly disagree) to 6 (strongly agree), with higher scores representing more intent to marry. Items include: "I intent to get married someday," "I want to marry," and "I do not hope to marry" (reverse scored). Cronbach's α was .84.

The Interpersonal Communication Motives Scale

To explore why college students communicate via Tinder, participants completed the Interpersonal Communication Motives Scale (ICM) (Rubin et al., 1988). The scale contains six subscales: Control, Relaxation, Escape, Inclusion, Affection, and Pleasure.

The scale consists of 28 Likert-type items that ranged from 1 (not at all like me) to 5 (exactly like me). Items for each subscale were summed and averaged. For this study, Cronbach's α for the subscales were: Control (.73), Relaxation (.87), Escape (.75), Inclusion (.83), Affection (.80), and Pleasure (.88). Table 1 contains the lists of all 3 items for each subscale as well as means and standard deviations of for male and female participants' communication motive items. The average used across each sub-item is summed together to obtain a composite score for the participants. Table 2 shows the Cronbach α for males and females.

RESULTS

To examine the first research question, whether there was a statistically significant difference in intent to marry between people who currently use Tinder ($M = 5.76$, $SD = 1.47$), as opposed to those who do not currently use Tinder ($M = 6.28$, $SD = 1.08$), an independent t-test was conducted. The test was significant, $t(279) = 3.31$, $p < .001$, suggesting that current Tinder users had significantly less intent to marry. Cohen's d was estimated at .62, which is a medium to large effect size (Cohen,1992).

To examine whether there was a statistically significant difference in attitudes toward marriage between people who currently use Tinder ($M = 4.84$, $SD = 1.10$) as opposed to those who do not ($M = 5.12$, $SD = .94$), an independent t-test was conducted. The test was significant, $t(259) = 2.06$, $p < .05$, indicating that current Tinder users had significantly more negative attitudes toward marriage. Cohen's d was estimated at .26, which is a small effect size (Cohen, 1992).

Table 1. Means and Standard Deviations for the Interpersonal Communication Motives Scale.

Items		Male [a] M	Male [a] SD	Female [b] M	Female [b] SD
I use Tinder….					
Pleasure					
1.	Because it's fun	5.12	1.33	4.88	1.55
2.	Because it's exciting	4.76	1.47	4.40	1.69
3.	To have a good time	5.08	1.42	4.48	1.72
Affection					
4.	To help others	3.00	1.65	2.31	1.46
5.	To let him/her know I care about him/her feelings	2.85	1.73	2.38	1.47
6.	To thank him/her	2.57	1.854	2.19	1.37
Inclusion					
7.	Because I need someone to talk to or be with	3.64	1.89	3.52	1.78
8.	Because I just need to talk about my problems	2.78	1.69	2.45	1.55
9.	Because it makes me feel less lonely	3.95	1.26	3.98	1.75
Escape					
10.	To put off something I should be doing	4.61	1.62	4.67	1.82
11.	To get away from what I am doing	4.42	1.57	4.05	1.75
12.	Because I have nothing better to do	5.15	1.49	5.15	1.68
Relaxation					
13.	Because it relaxes me	3.93	1.66	3.19	1.58
14.	Because it allows me to unwind	3.99	1.58	3.68	1.65
15.	Because it's a pleasant rest	4.37	1.57	3.60	1.72
Control					
16.	Because I want him/her to do something for me	3.91	1.16	2.78	1.74
17.	To tell him/her what to do	2.67	1.54	2.19	1.30
18.	To get something I don't have	4.31	1.51	3.52	1.86

[a]N = 83. [b]N = 204.

Table 2. Cronbach α's for the Interpersonal Communication Motives Scale.

I use Tinder….	Males	Females
Pleasure	.87	.88
Affection	.80	.80
Escape	.75	.76
Relaxation	.87	.87
Control	.73	.74
Inclusion	.83	.84

For the second research question, an independent t-test examining the differences between men and women and their communication motives for using Tinder showed significant differences between men and women with regard to their the motives of affection, escape, and control. Men were more likely than women to use Tinder for affection, $t(274) = 5.96$, $p < .05$; escape, $t(274) = 4.88$, $p < .05$, and control, $t(274) = 7.04$, $p < .05$. Cohen's d for the affection motive was estimated at .35, which is a small effect size. Cohen's d for the escape motive was estimated at .11, which is a very small effect (Cohen, 1992). However, Cohen's d for the control motive was estimated at .62, which is a medium to large effect size based on Cohen's guidelines (1992). See Table 1 for mean differences for each item of the communication motives scale.

For the third research question, participants were grouped into two categories: (1) college aged (18-22) and (2) anyone 23 or older. An independent t-test was conducted and showed that older young adults ($M = 14.95$, $SD = 3.08$) use Tinder significantly more for pleasure $t(254) = 6.91$, $p < .05$ compared to college aged adults ($M = 13.95$, $SD = 4.36$). Cohen's d was estimated at .26, which is a small effect size (Cohen,1992).

DISCUSSION

Lined up to the Uses & Gratification Theory proposed in the literature review section, the purpose of the present study was to explore and describe the particular relationship expectations and communication motives that may explain users' preference for Tinder for dating. As research on technology design indicate (e.g., Pusillo & Casini, 2014; Tuch, et. al., 2012), the description of users' intentions to use a given media goes beyond its taxonomic nature: it becomes an efficient measurement of the user experience of interactive products, and it is one of the first considerations for technology design in terms of hardware and software that impact any CMC device popularity (Cecere, et. al., 2015), because the design itself should suggest use for an specific experience otherwise users may not use it Puscillo & Cascini, 2014). Our findings reveal that current Tinder users have a significant difference in terms of relationship expectations than non–users; this is important because users stablish goals before engaging with a given media, and these goals are evaluated in terms of its extent in which mirror the original internal representations (i.e., expectations and motives) of the desired outcome (Wilson, 2015). Specifically, current Tinder users had less intent to marry and more negative attitudes toward marriage; additionally, these attitudes and intentions may in part explain the appeal for an app with less in-depth personal profiles and more focus on immediate impressions based on appearance in photos.

Individuals may not screen and scrutinize short-term dates in the way that they do long-term partners (Buss & Schmidt, 1993). Consequently, tethered to Whitty (2008) our results suggest that the structure in which information is accessed and sent in Tinder appear to be highly suitable for this type of goals compared to the heavy text and old fashioned combination of visuals and text embedded in other and previous online dating services, and this specific structure seem to prompt short term relationships expectations because of its emphasis on the visual information aspect. Therefore, our findings also corroborate to socioemotional selectivity theory, because current Tinder users with less intent to marry seem to be interested in using the app to fulfill short-term connections that boost their self–esteem and allow them to explore the social world.

This research further explored communication motives, with inquiry about possible female and male differences in communication motives. Based on an individual breakdown of the scale items, men reported they “talk to others on Tinder to get something that they don’t have” more so than females. That something might refer to sex, but it also might be referring to a romantic connection. The communication motives scale is insightful because it is important to understand why others chose this medium to communicate with others. Most importantly, men reported using Tinder more than women for the motives of affection, control, and escape. Tinder allows male users a way to approach partners without the FTF potential humiliation or rejection. Indeed, Tinder’s CEO, Sean Rad, claims that Tinder takes rejection out of dating. Further, men may be able to find several partners in a rapid fashion also explaining the findings that males are more likely to use Tinder than females for reasons linked to the same motives aforementioned.

The online dating experience seems to be enhanced through smartphone technology, because users’ perceptions of psychological and physical proximity are almost reduced to zero while using mobile devices compared to computer devices (e.g., Xie & Newhagen, 2012). Thus, the sensation of being there for dating is heightened to the maximum level giving users the perception of quickly achieving their original relationship expectations and communication motives. And this is reflected on the Cohen’s effect size obtained for users’ intent to marry which was moderate to high indicating that users with more short–term expectations fits better with the app as a recursive association.

Swann (2015) noted that older adults were not using that app due to age discrimination. Older adults tend to be more comfortable with FtF interactions. It would make sense that Tinder may be seen as a pleasure motive for older adults because for older adults Tinder is fun to use, it is exciting, and it provides for a good time; notwithstanding, our Cohen’s size was low compared to intent to marry score, and this may indicate that the short–term expectation is the overall more powerful intrinsic motivation that separates Tinder’s users from other dating apps.

CONCLUSIONS

Our findings seem to be competing with Sumter et. al., (2017), because for this study users with less intent to marry –understood as less level of romantic commitment, not only to the actual willingness of getting married– are considered to have short–term romantic intentions. Thus, for this study, less romantic commitment does not go beyond the hook up culture, and it is believed that the nature of attachment relationships has important denouements in romantic relationships: first because self–efficacy in romantic relationships (SERR) has been found to be predictive of current relationships outcomes (see for a review Riggio, et .al., 2013); second, research has also shown that “the longer couple members had known each other before they started dating, the less likely they were to be matched for attractiveness […] and [T] this moderator (i.e., attractiveness) reinforces the point that relationship initiation and maintenance must be understood as parts of the same continuous process in humans; to consider these two relationships stages separately may preclude a complete understanding of human naming” (Hunt, et al., 2015,p. 1048).

On the other hand, in terms of affection, escape, and control motives, men reported to displayed more. Specifically, the control motive was estimated at .62 showing a large effect on the basis of Cohen's guidelines. This may reflect an attempt to seize and control the gender role during romantic initiation in which men ask, and women decide; nonetheless, this may indicate an accentuation of traditional gender roles which is not desirable for our society. This study was not an attempt to lambast Sumter, et. al. (2017) analysis, but only to bring in attention on avoiding naïve conclusions that end up overlooking potential future risks derived from online dating use. Moreover, because of the current media consumption and the need of incorporating interpersonal communication theories to CMC and media effects research (Jeffres, 2015), it is crucial to cross validate online dating research with speed dating research and other FtF dating modalities.

As with all research, the current study is not without limitations. First, our measures of communication motives and relationship expectations were embedded into a larger survey that averaged about half an hour to complete. Therefore, the length of the questionnaire invites the possibility of fatigue. Second, the sample was predominantly female, and composed primarily of college students. Future research should ascertain the generality of our findings using samples of other demographic makeups. Third, even though participants were told that the study was confidential and anonymous, Tinder is typically perceived as a "hook-up" app to obtain sexual partners. Thus participants could have been providing socially desirable answers. However, social desirability should have led to fewer participants, and a majority of our participants reported using Tinder at least once.

Further, drawing conclusions about relationship behavior likely requires the measurement of actual behavior. Future researchers should gather the Tinder messages that are exchanged between the sender and the receiver of the message(s). What specifically do people communicate to their Tinder partners to convey that they want a sexual and/or romantic relationship? Does channel matter at all in this romantic pursuit (e.g., text messaging, Facebook, face to face)? How do motives, relationship expectations, and apprehension appear when one accounts for actual behavior? Is there truly a difference between relationship status and perceptions of Tinder, because most people who use Tinder are single rather than married? These are interesting questions and a logical next step for Tinder research. In addition, to access the impact of the technology device on online dating outcomes, researchers should explore the difference between personal computers and mobile devices.

IMPLICATIONS FOR RESEARCH

The analysis of relationships expectations and communication motives serve to understand why users choose a given online dating venue, and, additionally, this also shed a light on considerations of interface design. In other words, the Uses and Gratifications theory may help to perform inverse engineering to comprehend the reasons behind specific CMC characteristics (e.g., age, gender, etc.) rather than simply describing users' intentions and goals, and this is an original contribution of the present study. Unfortunately, the current understanding of interactivity is tethered to the CMC device itself rather than as an experience between the users and the event; consequently, users are not always aware of how the specifics characteristics and architecture of an online dating app or site affect them or why it appeals to them (Arias, et al., 2017; Finkel et. al., 2012). Furthermore, the present study is recursive in nature, but it is important to consider that CMC technologies influences also in a non– recursive way, then the normalization and standardization of online dating as "a new way of romantic initiation" should not be seen without empirical criticism. Our findings show how the Tinder app relates to individuals' relational expectations and communication motives, but also Tinder may affect other users' expectations and motives as MMT posits through an easy way for individuals to find potential romantic/sexual partners. It is important to understand how Tinder is different from other online dating sites/apps because its design was not done by chance, and how these differences may affect relationships initiation and development. Longitudinal studies are needed to compare the impact of using online dating apps of this type to others, and experimental research is required to establish how Tinder specific affordances impact users' emotions, expectations, and motives. Results from this study indicated that perceptions of relationship expectation and motives influence dating app use.

ENDNOTES

1. This false impression refers to the endowed progress effect (see Nunez & Dreze, 2006), which refers to when individuals are provided with artificial advancement to perform a given task, the task is reframed in a way that goal completion is redirected to persistence giving a false perception of completion.
2. In addition, the decision field theory shows that as the number of choices increases, the quality decisions decreases (see for a review Jessup, Veinott, Todd & Busemeyer, 2009).
3. Hand-held devices refers to any kind of electronic communication devices that can be used anywhere at any time such as tablets, smartphones, androids, etc. (Xie & Newhagen, 2014).
4. The term "Apps" is shorthand for "application"; Apps constitutes software that can be run on any electronic device which also may include GPS technology (Quiroz, 2013).
5. Thus, in addition to the three main features, the new version of online dating provide potential candidates' profiles to users on the basis of users' location proximity convenience.

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DECODING THE INTERFACE: EXPLORING WOMEN'S PERSPECTIVES ON INTEGRATING AI IN PROFESSIONAL WORK

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Abstract: *AI's impact on jobs varies by gender, with women facing higher replacement risks. This discrepancy is intensified by the digital divide, insufficient knowledge and skills, and a less open attitude towards AI among women, thereby limiting women's access to AI-driven opportunities. This paper's primary objective is to scrutinize women's self-assessment of digital competencies when utilizing AI in professional settings. Drawing from a survey conducted among Polish women, our findings reveal that the adoption of AI is linked to factors such as age, education, work experience, and location of residence. Women with higher levels of education residing in larger cities, as well as younger individuals with less work experience, are more likely to recognize the advantages of utilizing AI. Their concerns are less about the necessity for continuous development of digital skills, but rather about the potential impact of AI on their work-life balance and the possibility of a decrease in earnings, despite the anticipated improvements in productivity and time management efficiency.*

Keywords: *AI, women, future of work, technological change.*

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INTRODUCTION

The rapid development of Artificial Intelligence (AI) is reshaping the landscape of technology and society at an unprecedented pace. Advances in machine learning, neural networks, and data processing have fueled an acceleration in AI capabilities. From revolutionizing industries with smart automation to enhancing personalized user experiences, the swift evolution of AI is fostering breakthroughs across various domains. As the technology continues to mature, its potential to drive innovation, solve complex problems, and augment human capabilities becomes increasingly profound, marking a transformative era in the digital age (Prieto-Gutierrez, 2023).

The current AI revolution, however, is marked by persistent challenges, including issues of gender-based discrimination (McNeilly, 2023), unequal compensation between men and women (WEF, 2023), and limited opportunities for women's career advancement. Digital literacy of the workforce and firms' digital literacy activities for their employees are some of the major concerns of the digitalization process (Krajčík et al., 2023). Stereotypes and societal expectations also contribute to the underrepresentation of women in specific industries and leadership positions, especially those requiring specific advanced digital skills (Woźniak-Jęchorek et al., 2023). In Europe, only 19% of ICT specialists and about one-third of science, technology, engineering, and mathematics graduates are female (Women in Digital, 2021). Moreover, the substantial challenge of balancing work and family responsibilities persists, often burdening women with caregiving duties (Bencsik & Juhasz, 2023; Ferrant et al., 2014). To break down these gender barriers, promote diversity, and create more equitable opportunities for women in the workforce, there is a need for an increased understanding and acceptance of generative AI (Gomes, 2022).

Previous research has shown, however, that support for developing AI varies greatly between demographic subgroups, with gender, education, income, and experience being key predictors (Karacsony et al., 2020; Zhang & Dafoe, 2019) as well as among managerial staff involved for the knowledge-based systems development (Bencsik, 2021). These issues often stem from leadership inadequacies and human resource management shortcomings (Plaikner et al., 2023). Although a majority supports AI development, the demographic largely in favor comprises primarily highly educated and affluent men. Additionally, gender disparities exist in the perception of AI, with women, as per self-awareness assessments, exhibiting a lower understanding of AI compared to men (Franken et al., 2020). Men, in contrast, see more opportunities in AI, rate their own AI competence higher than women, and trust more in AI. Developing one's own AI competence removes fears and promotes trust and acceptance towards AI – an important prerequisite for openness towards AI (Franken & Mauritz, 2021).

AI has the potential to transform the way work is conducted, making it more efficient, intelligent, and adaptable to the evolving demands of the modern workplace. However, a challenge arises in the acceptance of AI in professional work, potentially stemming from a lack of a thorough understanding of AI technologies and their implications, and the ethical implications of AI, including algorithmic bias, privacy concerns, and the potential for job displacement (Zirar et al., 2023).

Therefore, this paper aims to investigate women's self-assessment of digital competencies when utilizing AI in professional settings. To assess women's AI competencies, we adopted the European Commission's definition of digital competence outlined in the DigComp 2.2

framework. Digital competence encompasses the "confident, critical and responsible use of, and engagement with, digital technologies for learning, at work, and for participation in society. It is defined as a combination of knowledge, skills, and attitudes" (DigComp 2.2, 2023). This approach is widely used for similar research of digital competences (Bilan et al., 2023). In the paper, we characterize women's AI competencies as the knowledge, skills, and capabilities that empower women to proficiently engage with and contribute to tasks related to artificial intelligence.

To explore women's perspectives on integrating AI in professional work, we surveyed Polish working women. The structure of this paper is as follows: we start by offering an overview of the recent studies presenting the implications of AI for the future of work, and then the impact of generative AI on women's jobs. The literature helps inform the design of our survey, described in the following section. Proceeding onward, we provide an account of the research findings and discussion with a summary of key takeaways.

Artificial Intelligence: Implications for the Future of Work

AI has become deeply integrated into various aspects of daily life and professional environments. Applications range from digital personal assistants and smart appliances to online shopping platforms and industrial robots. Despite concerns from some experts about the regulatory framework surrounding AI (EC, 2023), its pervasive use is undeniable, shaping the future of work.

The collaboration between AI and human workers is an evolving landscape, giving rise to two primary issues. First, AI's capacity to automate routine tasks raises concerns about potential job displacement and a reduced workforce. Nevertheless, existing research has not yet built a solid view of the definitive impact of AI on jobs. For instance, Big Tech layoffs claimed more than 150,000 jobs throughout 2022 alone, with Goldman Sachs predicting that 300 million jobs will ultimately be lost or degraded by artificial intelligence (Goldman Sachs, 2023). A Forbes Advisor survey indicates that 77% of individuals express apprehension about AI causing job losses (Haan & Watts, 2023), with McKinsey estimating that the evolution of AI could displace 400 million workers globally (Manyika & Sneader, 2018). The World Economic Forum's Future of Jobs Report (2023) predicts a negative impact on 25% of jobs over the next five years, particularly in administrative roles, legal services, architecture, engineering, business operations, management, sales, healthcare, and art and design. Past automation technologies had the most effect on low-skilled workers. But with generative AI, the more educated and highly skilled workers who previously were immune to automation are vulnerable. ILO suggests in turn that most jobs and industries are only partly exposed to automation and are more likely to be complemented rather than substituted by the latest wave of generative AI (Gmyrek et al. 2023).

The literature on automation and jobs, which primarily focuses on OECD countries, tries to identify job-level tasks that could be replaced by machines and then estimate the macro-level effects of such a replacement (Frey & Osborne 2017; Brynjolfsson et al., 2018; Felten et al., 2018; Acemoglu & Restrepo 2020, 2022; Fossen & Sorgner, 2022). According to the International Labor Organization, there are between 644 and 997 million knowledge workers globally, between 20% and 30% of total global employment (Berg & Gmyrek, 2023). The labor market of these individuals may be somehow impacted by generative AI.

Despite fears of job displacement, projections indicate that automation will lead to the creation of numerous new jobs. In 2022, 39% of businesses hired software engineers, and 35% recruited data engineers for AI-related positions. AI is expected to generate approximately 97 million new jobs (Workplace, 2023). Importantly, AI is not automating all functions but primarily focuses on routine tasks, leaving room for human oversight and intervention (Mitchell & Brynjolfsson, 2017).

Rather than replacing humans, AI is envisioned to collaborate with them, enhancing efficiency and allowing workers to concentrate on more creative and fulfilling aspects of their roles (Zirar et al., 2023). The greatest impact of this technology is likely to be the potential changes to the quality of jobs, notably work intensity and autonomy (ILO, 2023). The advent of AI creates, however, a heightened demand for individuals with technical skills, including programmers, statisticians, data scientists, and analysts, as well as those possessing creative and emotional intelligence.

As organizations increasingly adopt AI, substantial changes in job functions necessitate strategies to showcase AI as a force for positive change. Emphasizing that AI is designed to complement human workers, not replace them, is crucial. Equally important is ensuring that the workforce possesses the necessary tech skills through upskilling and reskilling initiatives, enabling them to harness the full potential of AI opportunities.

Could Generative AI Have a Disproportionate Impact on Women's Employment?

The International Labor Organization (Gmyrek et al., 2023) states that the potential for AI to replace jobs is disproportionately higher for women worldwide, estimated at around 4%, compared to only 1% for men. The impact of artificial intelligence on working women is, however, multifaceted, with both opportunities and challenges. On one hand, AI has the potential to create more inclusive and flexible work environments, providing women with tools to enhance productivity and streamline tasks. However, concerns about the automation of certain job functions could also pose challenges, requiring a proactive approach to reskilling and upskilling to ensure women are well-equipped to navigate the evolving job market.

Women may exhibit a greater reluctance towards AI, primarily due to their increased vulnerability to automation by generative AI compared to men. According to McNeilly (2023), a significant majority of women in the U.S. workforce, accounting for eight out of ten (58.87 million), are engaged in occupations with high exposure to generative AI automation (involving more than 25% of occupational tasks). In contrast, six out of ten men (48.62 million) face similar exposure. Despite men outnumbering women in the workforce, the data reveals that women experience a 21% higher exposure to AI automation than their male counterparts. This discrepancy is even more pronounced in high-income countries, where 8% of female jobs face the threat of automation, contrasting with 3% of male jobs. Analyzing the U.S. labor market, nearly 80% of women in the workforce are in occupations exposed to automation via generative AI, whereas this figure stands at 58% for men (McNeilly, 2023). The primary reason for this gender disparity lies in the occupational distribution, with a higher percentage of women engaged in white-collar jobs (approximately 70%) compared to blue-collar roles (around 30%), while the ratio for men is roughly 50/50.

Despite women constituting nearly half of the global population, a significant gender gap still exists in internet usage, with 259 million fewer women accessing the internet than men (ITU, 2022). This digital divide is particularly notable in lower-income nations, where only 21% of women are online compared to 32% of men. Cultural and social norms, unsafe access routes to public ICT facilities, and financial constraints contribute to this disparity. In Poland, as well as in Romania, Bulgaria, Hungary, and Italy, women also exhibit the lowest levels of participation in the digital economy and society (Women in Digital, 2021). Poland, known for strong female representation in STEM (Science, Technology, Engineering and Mathematics), faces challenges in gender diversity in the tech industry, with only 16.7% of women employed in the sector (globally, 29% of women are employed in STEM roles) (WEF, 2023). Despite having in Poland almost 43% of female STEM graduates, not all of them pursue careers in technology, as revealed by the Women in IT report by No Fluff Jobs (2023). Poland ranks 24th in AI intensity in the active workforce in the EU, with 13% of AI employees being women. The underrepresentation of women is evident in AI teams globally, with a third of companies having all-male teams. World Economic Forum estimates that in the AI workforce, women constituted only around 30% as of 2022, reflecting a modest four-percentage point increase since 2016 (WEF, 2023). Being a part of the tech industry is one challenge, but another one is to collaborate with AI, to enhance efficiency and allow women to concentrate on more creative and fulfilling aspects of their lives.

METHODS

To examine women's self-assessment of digital competencies when utilizing AI in professional settings, we surveyed Polish women. In pursuit of our goal, we address two primary research inquiries:

1. What is the perception of women regarding the potential for AI collaboration within a professional setting (RQ1)?
2. Given previous research shows male support of AI development, are women willing to accept such collaboration in their workplace (RQ2)?

Data collection was performed through a survey questionnaire, comprising three sections: 1) knowledge, 2) skills, and 3) attitudes, each containing a set of questions, and distributed to an online quota sample consisting of 630 full-time working women. These participants were drawn from the pool of respondents recruited online by Ariadna (the biggest independent nationwide research panel in Poland) in November 2023 (please refer to Appendix for additional details). A survey with 630 respondents is designed to achieve a confidence level of 95%, a maximum margin of error of 0.04%, and a fraction size of 0.5, considering the reported 7.1 million employed women in the national economy of Poland as of February 2023 (GUS, 2023).

In the first part of the questions, we inquired about women's perspectives on how the utilization of AI might influence various facets of their professional lives. We sought their opinions on the current deployment of AI in specific occupations, along with their insights into how AI could support them in their professional roles. Additionally, we formulated two inquiries regarding the future, prompting women to identify the areas they deem most vital for AI application and those where they perceive no need for developing digital skills, anticipating the assumption that AI algorithms will assume control. Subsequent questions focused on evaluating women's proficiency in digital skills concerning basic and advanced professional activities, as well as their capabilities in decision-making and problem-solving contexts using AI. Lastly, two questions delved into women's attitudes, exploring aspects of acceptance and confidence in AI utilization, along with any apprehensions about its application in diverse contexts.

RESULTS

Initially, we explore women's perspectives on the potential impact of AI on different facets of their professional lives. Figure 1 illustrates that, concerning various work aspects, women believe that AI's influence is most pronounced in the areas of fostering digital skills and supporting ongoing education, while its impact appears to be less significant on their standing in the labor market (please refer to Appendix for additional details). The opinions expressed by women may be grounded in their educational background and workplace experiences, such as exposure to AI technologies, training programs, or changes in job responsibilities. Within our sample, a significant percentage holds advanced degrees 67.78%, while another substantial percentage is employed in industries with AI applicability (IT 5.87%, Finance and Banking 11.27%, Industry 12.54%, Education 13.33%, and Trade and Services 27.14%). The broader public viewpoint is additionally susceptible to the portrayal of AI in the media. The ongoing discourse concerning the necessity for both upskilling and deskilling can further shape these viewpoints.

Examining the domains in which women perceive AI as beneficial in their professional endeavors (Figure 2), they assert that AI has the potential to enhance the efficient use of working time, automate office activities, improve access to digital resources through faster information processing, and increase work productivity. Notably, women do not believe that AI significantly contributes to boosting self-confidence in executing professional duties or improving work-life balance through quicker and less engaging tasks. Interestingly, their average rating of self-confidence in decision-making and problem-solving in their professional context surpasses their overall confidence in using AI at work (Figure 3). Furthermore, an analysis of the flow of survey responses regarding overall confidence, acceptance of AI, and self-confidence (Figure 4) reveals that women with very high and high acceptance of AI at work often exhibit moderate overall confidence and self-confidence. Additionally, there are instances of women with high or moderate acceptance but with moderate overall confidence and high self-confidence.

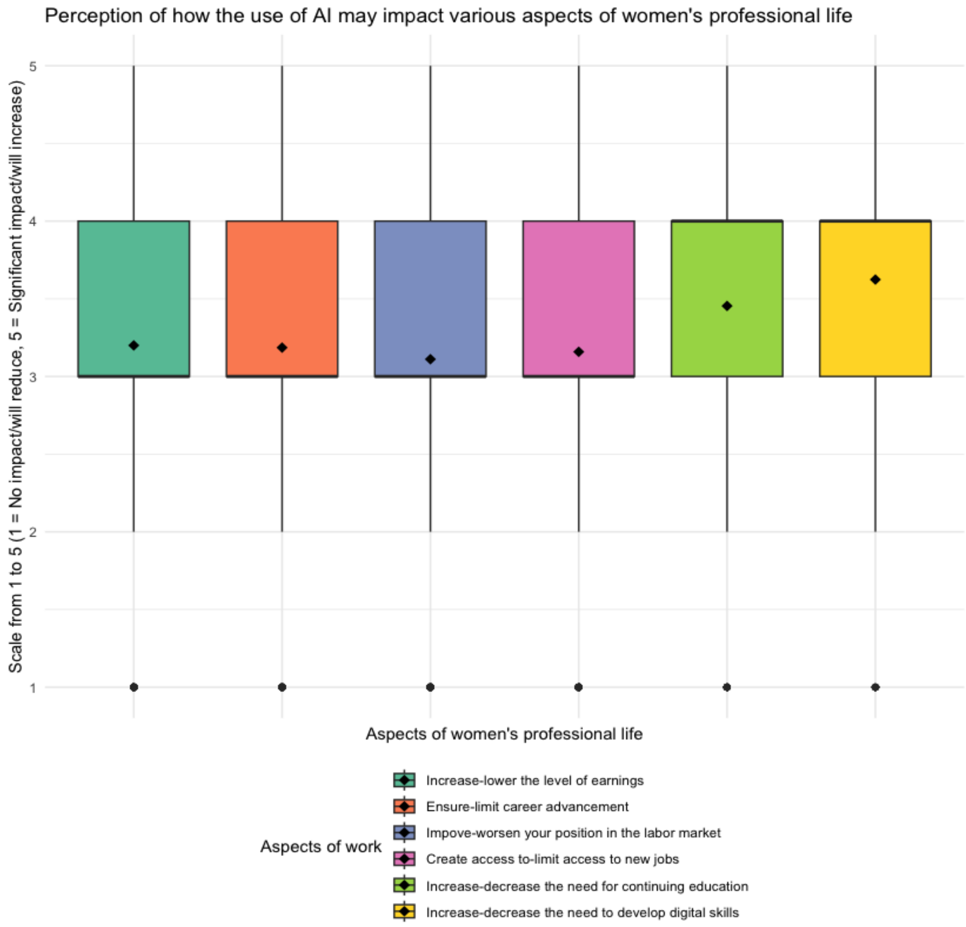

Figure 1. Perception of how the use of AI may impact various aspects of women's professional life. *Note*: The box represents the interquartile range (IQR) of the data, which includes the middle 50% of the values. The bottom and top edges of the box represent the first (Q1) and third (Q3) quartiles, respectively. The line inside the box represents the median (Q2) of the data, and the mean points represent the mean value of each group. Individual points outside the whiskers represent potential outliers – observations that fall significantly outside the typical range of values. The whiskers extend from the edges of the box to the minimum and maximum values within a certain range (usually 1.5 times the IQR).

Source: own elaboration.

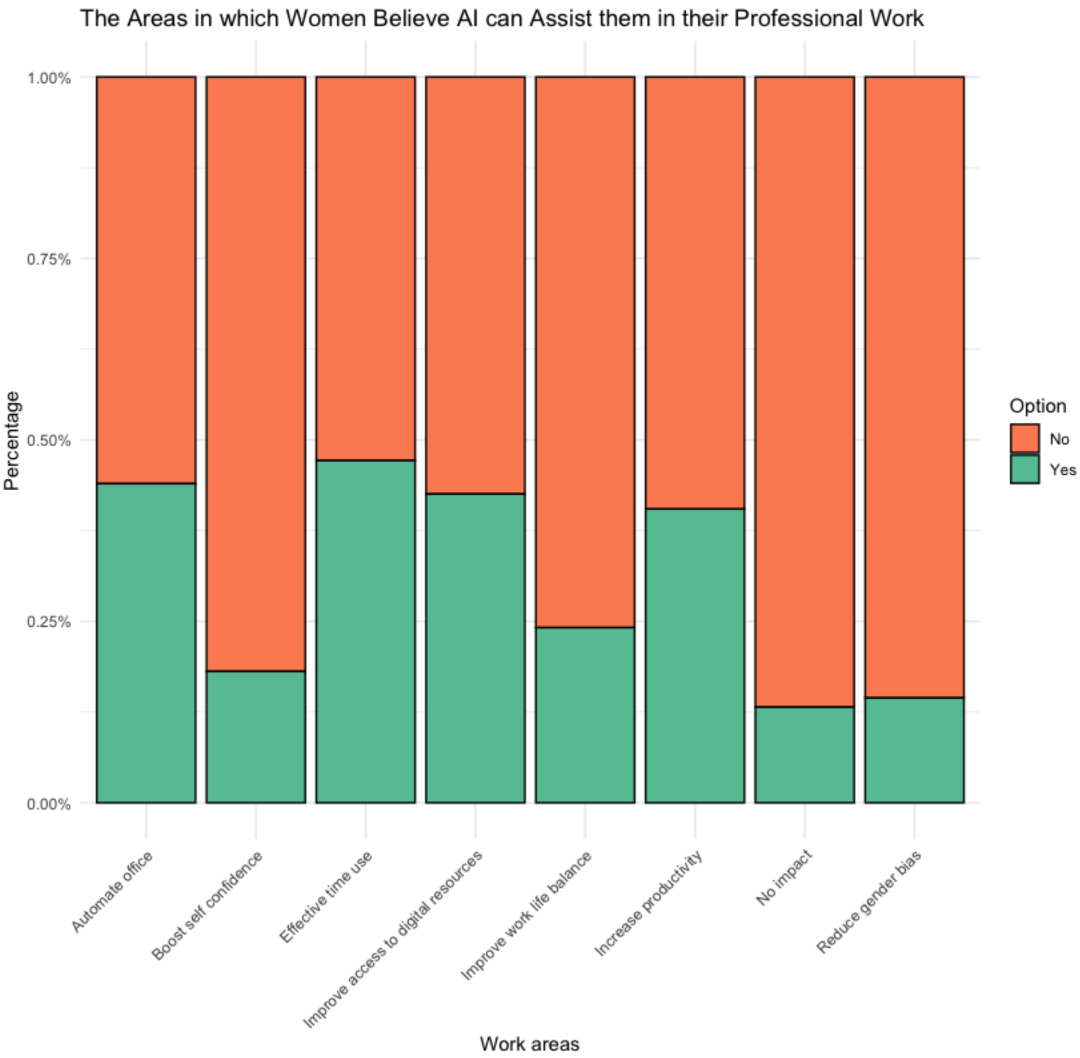

Figure 2. The areas in which women believe AI can assist them in their professional work. Source: own elaboration.

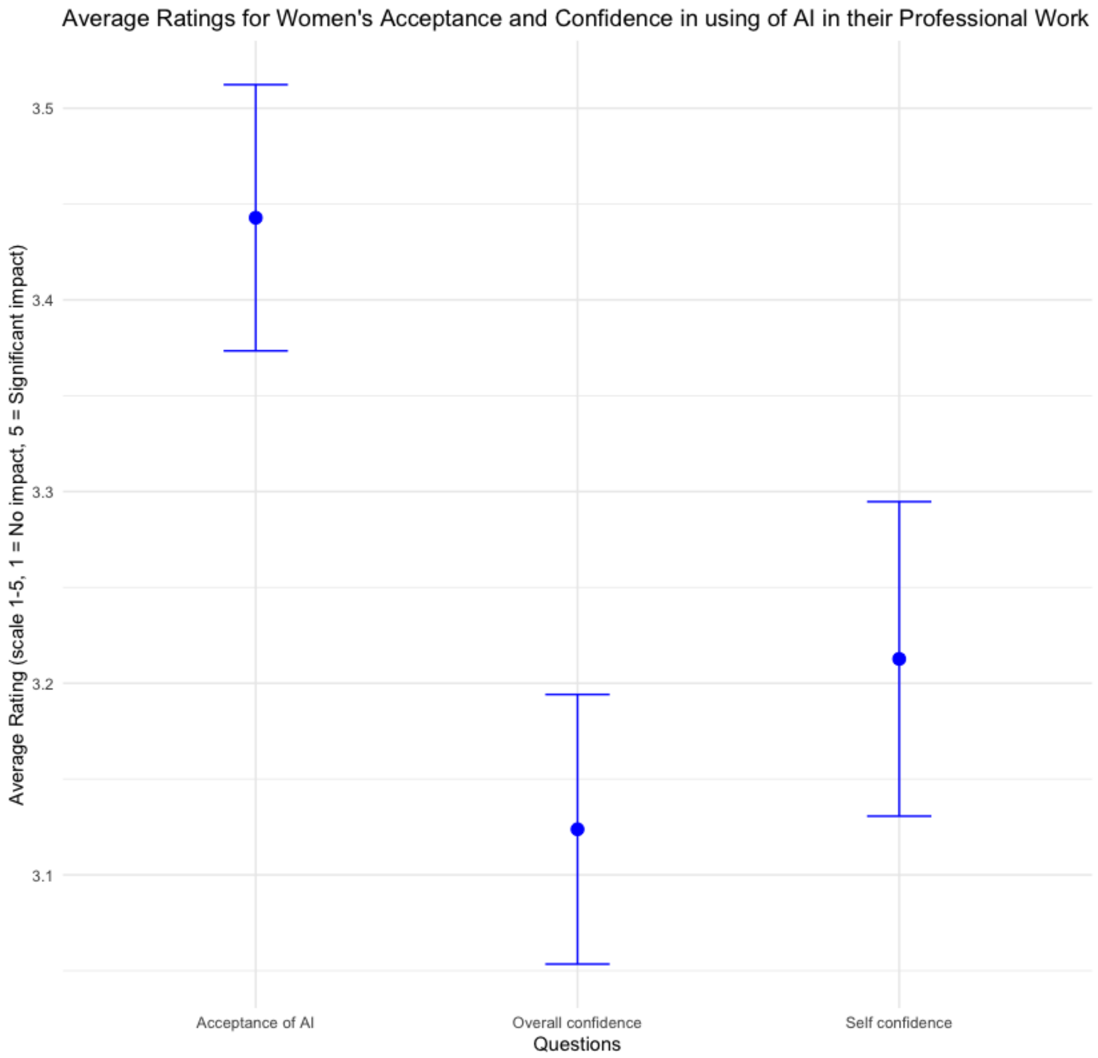

Figure 3. Average ratings for women's acceptance and confidence in using AI in their professional work. Note: The information provided is derived from the evaluations of how the application of AI impacts women's self-confidence in decision-making and problem-solving within their professional sphere; the assessments of the degree of acceptance of AI in women's professional endeavors and evaluations of their overall confidence in utilizing AI in their professional activities.
Source: own elaboration.

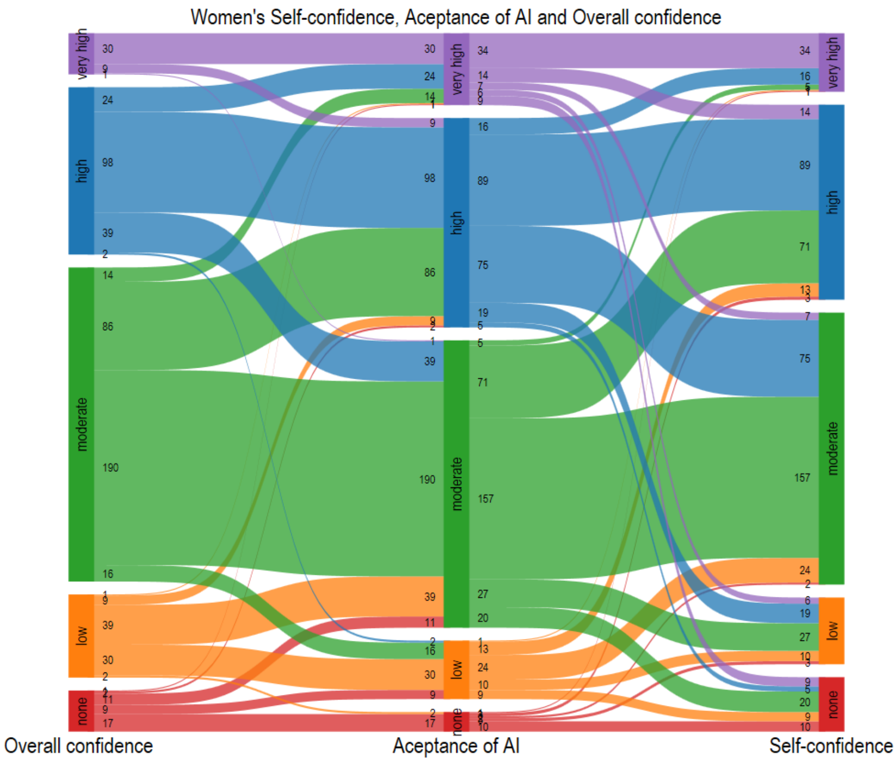

Figure 4. Alluvial plot of women's overall confidence, acceptance of AI, and self-confidence
Note: Based on three survey questions: rating of the impact of AI use on women's self-confidence in decision-making and problem-solving at work, rating of AI acceptance in their professional work, and rating of overall confidence in using AI in their professional work.
The alluvial diagram demonstrates the flow of survey responses between different questions and helps to understand the relationships between these categories. The three vertical axes represent Overall Confidence, Acceptance of AI, and Self-confidence. The labels on each axis indicate the levels within each axis. The flow of streams from one stratum to another shows the movement or transition of observations across different combinations of values.
Source: own elaboration.

The relationship between acceptance of AI, overall confidence, and self-confidence appears to be complex. Women who express very high or high acceptance of AI at work tend to demonstrate a moderate level of overall confidence and self-confidence. This could indicate that, despite embracing AI technologies in the workplace, these individuals may maintain a balanced or cautious level of overall confidence and self-assurance. Moreover, the correlation between high acceptance of AI and moderate confidence levels might suggest that the introduction or acceptance of AI in the workplace does not necessarily translate to an extreme boost in overall confidence or self-confidence. In turn, the instances of women with high or moderate acceptance but with moderate overall confidence and high self-confidence highlight individual variances. It suggests that acceptance of AI does not uniformly align with confidence levels. Factors such as personal experiences, job roles, or specific contexts may contribute to these individual differences. These findings could reflect a nuanced stance where women may be embracing AI for certain aspects of their work while maintaining a measured level of confidence. There might be a balance between leveraging AI technologies and maintaining a level of self-assurance in specific professional domains. These observations suggest a need for further exploration and understanding of the interplay between acceptance of AI and confidence levels.

We have also explored the perspectives of women concerning their perceptions of which professions currently utilize AI. To evaluate these beliefs, we compared them with the predictions made by Goldman Sachs regarding the exposure of occupations and tasks to AI automation (refer to Table 1). It appears that Polish women do not perceive AI's role in occupations related to farming, fishing, and forestry (8.6% positive responses versus a predicted 28% employment at risk of automation by Goldman Sachs) and legal professions (19.5% versus 44%). Conversely, they do acknowledge the involvement of AI in business and financial operations (53.3% versus 35%) and education, instruction, and library-related roles (38.1% versus 27%).

Table 1. Occupations and Task Exposure to AI Automation – Goldman Sachs predictions and survey findings

	Goldman Sachs prediction	Survey findings
Office and Administrative Support	46%	50.5%
Legal	44%	19.5%*
Architecture and Engineering	37%	37.6%
Life, Physical, and Social Science	36%	-
Business and Financial Operations	35%	53.3%
Community and Social Service	33%	23.8%
Management	32%	28.6%
Sales and Related	31%	33.8%
Computer and Mathematical	29%	-
Farming, Fishing, and Forestry	28%	8.6%
Protective Service	28%	29.2%
Healthcare Practitioners and Technical	28%	21.7%
Educational Instruction and Library	27%	38.1%
Healthcare Support	26%	-
Arts, Design, Entertainment, Sports, and Media	26%	31.9%

Note: The proportion of affirmative responses in the query prompting women to specify the professions where they believe AI is currently utilized. Multiple options can be selected.
* The understated result may be due to the limited representation of female lawyers in our research sample.
Source: own elaboration based on Goldman Sachs (2023) and survey findings.

In another question, we have examined the concerns expressed by women regarding the utilization of generative AI. It appears that the primary concerns among Polish women revolve around the costs associated with implementing AI systems and new technologies within their companies, as well as the lack of transparency and challenges in comprehending AI algorithms (Figure 5). In contrast, there is relatively lesser apprehension about dependency on technology and the potential loss of the ability to engage in creative work. Notably, the larger size of the box associated with this latter concern implies a greater spread or variability of data within this specific category compared to others. This suggests that the opinions regarding the impact of AI on creative work vary more widely among the respondents compared to the concerns about other aspects of generative AI.

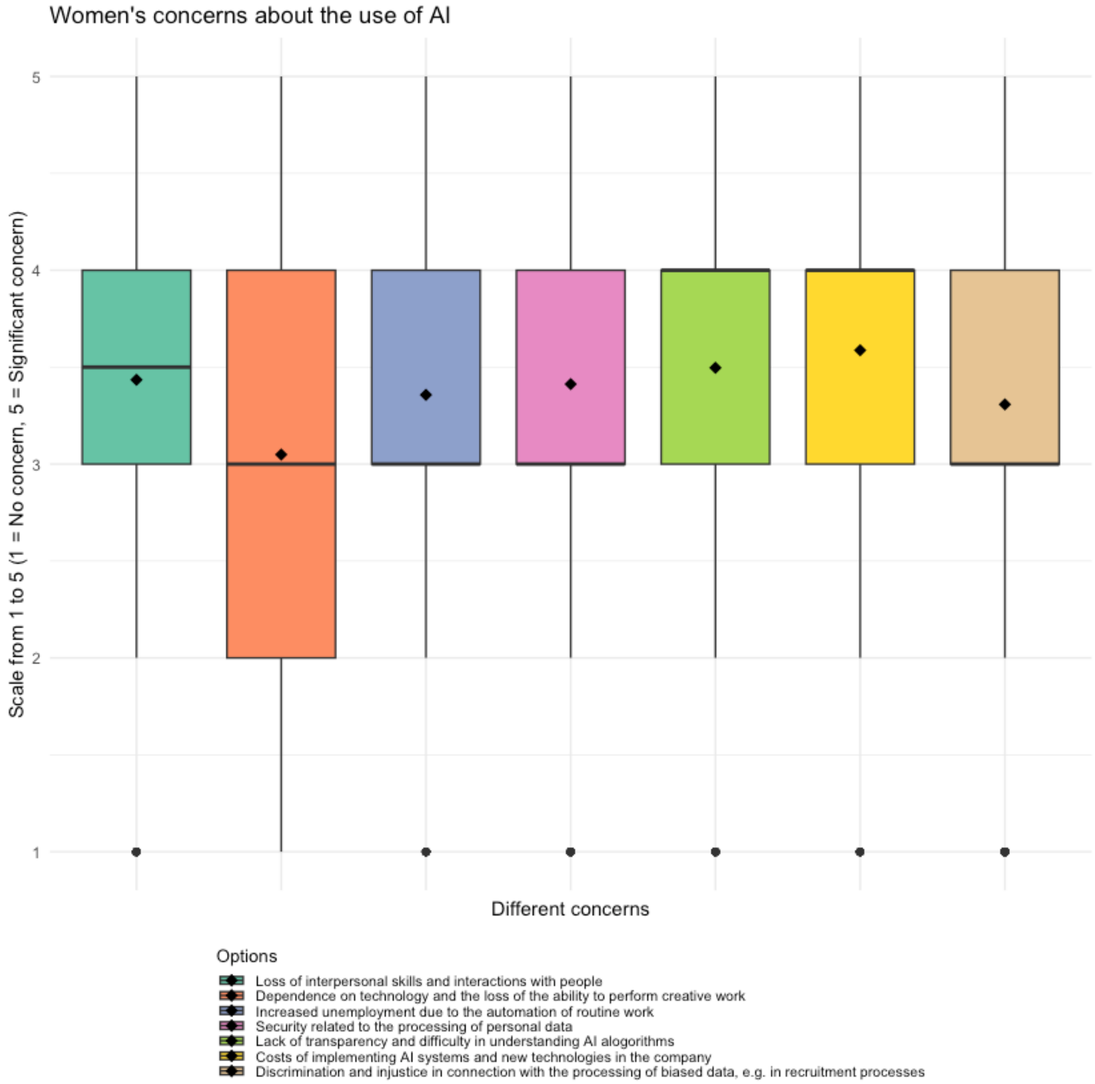

Figure 5. Women's concerns about the use of AI

Note: The box represents the interquartile range (IQR) of the data, which includes the middle 50% of the values. The bottom and top edges of the box represent the first (Q1) and third (Q3) quartiles, respectively. The line inside the box represents the median (Q2) of the data, and the mean points represent the mean value of each group. Individual points outside the whiskers represent potential outliers—observations that fall significantly outside the typical range of values. The whiskers extend from the edges of the box to the minimum and maximum values within a certain range (usually 1.5 times the IQR).

Source: own elaboration.

Lastly, we have investigated the domains in which women perceive that developing digital skills is dispensable, as they anticipate AI algorithms to assume control. It appears that customer services, payment processing, artistic professions, and graphic design are the fields where the development of digital skills is deemed unnecessary (Figure 6). Notably, artistic professions, including Arts, Design, Entertainment, Sports, and Media occupations, are unexpectedly included in this category. Interestingly, Polish women also identified these occupations as being most impacted by AI, aligning with Goldman Sachs' prediction (31.9%

versus 26%) (Table 1). There may be a lack of clarity or understanding among women about how AI is implemented in creative fields. On the other hand, creative processes often involve complexity, unpredictability, and a high degree of personal expression. Women may perceive these elements as challenging for AI to replicate, leading to the belief that developing digital skills is unnecessary in these areas.

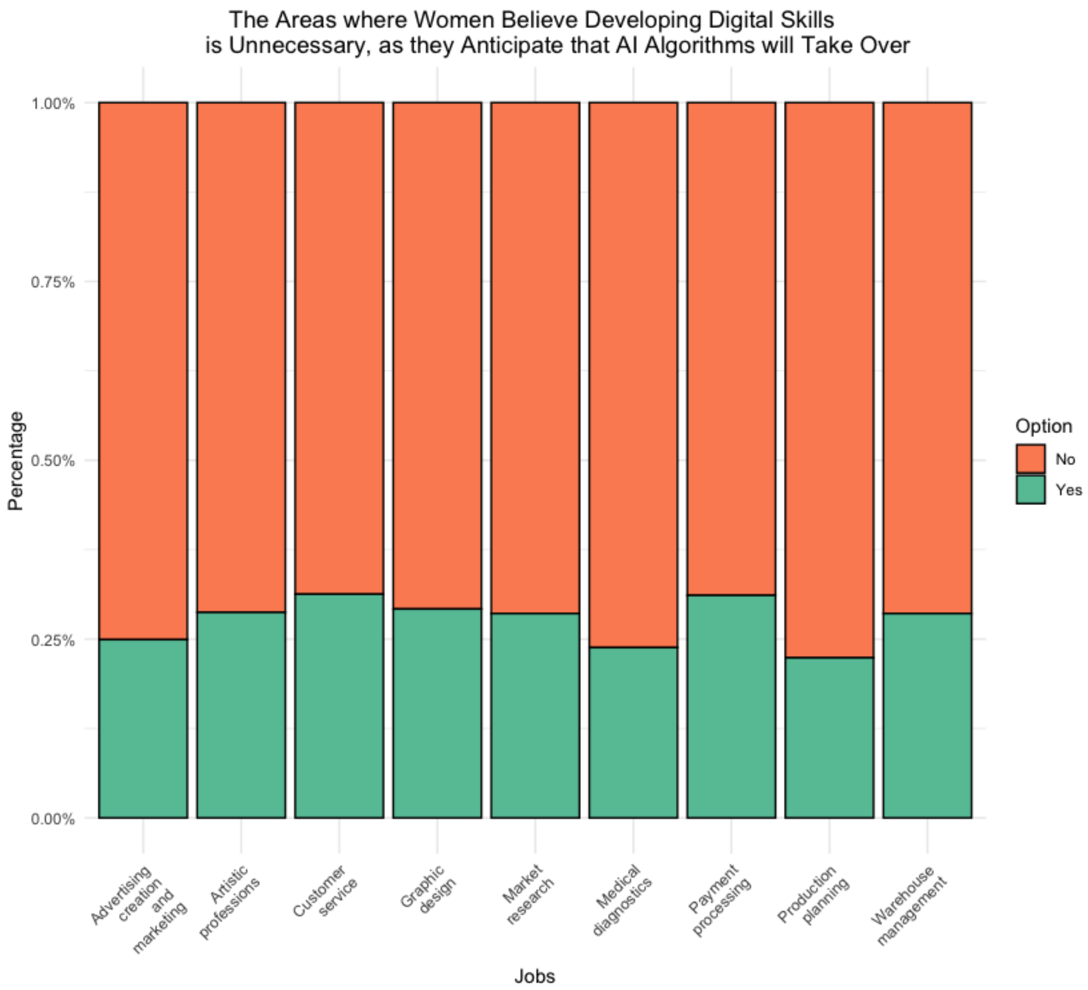

Figure 6. The areas where women believe developing digital skills is unnecessary, as they anticipate that AI algorithms will take over
Source: own elaboration.

DISCUSSION

In addressing the two research questions of this study about women's perception of AI collaboration within a professional setting (RQ1) and their acceptance of such collaboration (R2), it becomes evident that women encounter challenges in understanding how AI functions.

Nevertheless, an exploration of AI utilization reveals correlations with variables such as age, work experience, place of residence, and education. Younger individuals and those with less work experience are more likely to declare the use of AI. Additionally, there is a notable trend of increased AI usage in larger cities and among individuals with higher education. However, women with higher education express concerns that AI usage may lead to a decrease in earnings and necessitate the development of digital competencies.

Notably, a comparison between responses from women who have and have not previously used AI yields interesting conclusions. Women utilizing AI exhibit stronger convictions that its use can enhance promotion opportunities, necessitate continuous learning, and contribute to the development of digital skills. Furthermore, these women express higher confidence in AI's ability to increase productivity and improve the efficiency of working time. However, they express less optimism about its potential to improve work-life balance and harbor reservations about its contribution to equal opportunities. Surprisingly, women using AI are more likely to report experiencing a lack of transparency and difficulties in understanding AI algorithms. Additionally, they harbor fears that the use of AI may result in the loss of personal skills and interpersonal relationships.

The acceptance level of AI use in professional work is found to be correlated with the experience of using AI. Higher-earning women from larger cities exhibit slightly higher declared acceptance of AI, and individuals in higher positions tend to believe that AI has no impact on self-esteem.

Our findings yield three significant insights into the existing literature. First, women's comprehension of AI algorithms appears to be more intuitive than explicit. This observation aligns with Franken et al.'s (2020) identification of gender disparities in AI perception, wherein self-awareness assessments indicate that women tend to have a lower understanding of AI compared to men. This discrepancy may stem from the underrepresentation of women in technology-related fields, disparities in educational opportunities, and limited access to STEM education. In Poland, societal stereotypes and cultural expectations can contribute to shaping perceptions of gender roles (e.g., Mandal et al. 2012), impacting women's involvement in technology and AI. Implicit biases and gender stereotypes also influence how women's contributions to AI discussions are perceived. Additionally, the workplace environment, encompassing mentorship availability, skill development opportunities, and a supportive atmosphere, plays a crucial role in shaping women's understanding of AI. Addressing these issues necessitates concerted efforts to promote diversity and inclusion in education, workplaces, and AI development.

Secondly, despite AI's recognized weaknesses in areas such as creativity, innovation, emotional intelligence, adaptability, and moral judgment, women surprisingly do not perceive the advantages of AI for work-life balance. In the context of the ongoing technological revolution (Industry 5.0), which prioritizes worker well-being and adopts a human-centric approach to digital technologies (EC, 2023), it is crucial for women to understand that AI can automate routine tasks, allowing for more focus on meaningful and creative aspects of work. AI's strengths in efficiency, speed, storage, recall, and physical capabilities contribute to optimizing time management and facilitating remote work. However, it is essential to note that ethical AI use, privacy protection, and ongoing monitoring are critical for harnessing the full benefits of AI in creating a balanced and sustainable work environment (OECD, 2022; Radanliev & Santos, 2023; EUR-Lex, 2023).

Third, the relationship between the acceptance of AI and confidence is not always straightforward. Possible reasons for this ambiguity include concerns about AI's impact on job security, fear of job displacement due to automation, and varying levels of understanding among women. Additionally, inadequate communication and education about the benefits and limitations of AI contribute to misconceptions and uncertainty. Public messages from social partners and policymakers, particularly in Poland where AI is often portrayed as a risk to job stability (Gov, 2020), shape this perception. Women, who have different risk tolerance, openness to new experiences, and attitudes toward change compared to men (Holden & Mesfin, 2018), require targeted education about the benefits of AI.

CONCLUSIONS

Research focused on women's self-assessment of digital competencies when utilizing AI in professional settings suggests a lower understanding of AI among women compared to men, leading to reduced acceptance and confidence in the new technology. While previous studies have shed light on demographic predictors influencing support for AI development, such as gender, education, income, and experience, there is a relative scarcity of comprehensive efforts to delve into the factors driving women's support for AI integration in their professional work. This explanatory study simultaneously explores women's perspectives on AI by examining their knowledge, skills, and attitudes toward the technology.

The findings presented in this paper draw from short-term and country-specific data, reflecting the ongoing and dynamic trends in the AI revolution. These trends have the potential to shape women's perceptions in the future. To gain a deeper understanding of how AI development will evolve in the long term and across different countries, further analysis is warranted. As generative AI becomes more ingrained in contemporary organizational life, establishing a robust and context-specific research agenda becomes crucial for aiding practitioners in navigating this potential future.

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Appendix

Respondent's socio-demographic characteristics

The data presented herein were gathered through Poland's Adriadna research panel, the largest independent nationwide research panel in the country. The online survey took place in November 2023 and yielded 630 valid responses. Respondents' basic socio-demographic characteristics included age, education level, place of residence, income, industry, position, experience in their current role, and sector of employment. An examination of the socio-demographic distribution among the 630 women partaking in the study unveils intriguing insights.

The study highlights a diverse age distribution, with a notable percentage falling within the 25-34 age range (40.48%). A significant portion of women holds higher education degrees (67.78%), while a smaller percentage completed secondary education (31.90%). Participants with primary education make up only a marginal percentage (0.32%). Residence categories vary, with a substantial portion residing in cities with populations ranging from 100,000 to 500,000 inhabitants (24.76%). Notably, 19.05% of women live in villages, reflecting a blend of urban and rural representation.

Income distribution reveals that the largest group earns between PLN 3501 to PLN 4500 net (33.81%), while 9.68% earn over PLN 7001. In terms of sectoral engagement, the trade and services sector attracts the highest participation (27.14%), followed by education (13.33%) and finance and banking (11.27%). Concerning positions, the majority of women hold office administrative roles (36.67%) or specialist positions (37.46%). A smaller percentage occupies managerial or directorial positions, and 13.65% fall under the category of "Other."

Experience distribution is fairly balanced, with significant percentages across various experience brackets. In terms of experience in their current position, a substantial portion of women (26.83%) report having more than 10 years of experience. Notably, a significant percentage of women work in the private sector (63.81%), while 36.19% are employed in the public sector.

Table A1. Tabulation of age

	Freq.	Percent	Cum.
18-24 years	23	3.65	3.65
25-34 years	255	40.48	44.13
35-44 years	184	29.21	73.33
45-54 years	110	17.46	90.79
55-60 years	43	6.83	97.62
61-65 years	13	2.06	99.68
66+	2	0.32	100.00
Total	630	100.00	

Table A2. Tabulation of the place of residence

	Freq.	Percent	Cum.
Village	120	19.05	19.05
City up to 50,000 inhabitants	133	21.11	40.16
City from 50,000 to 100,000 inhabitants	82	13.02	53.17
City from 100,000 to 500,000 inhabitants	156	24.76	77.94
City over 500,000 inhabitants	139	22.06	100.00
Total	630	100.00	

Table A3. Tabulation of income

	Freq.	Percent	Cum.
below 3500 net	151	23.97	23.97
from 3501 to 4500 net	213	33.81	57.78
from 4501 to 5500 net	122	19.37	77.14
from 5501 to 7000 net	83	13.17	90.32
over 7001	61	9.68	100.00
Total	630	100.00	

Table A4. Tabulation of industry

	Freq.	Percent	Cum.
Agriculture and breeding	11	1.75	1.75
Industry	79	12.54	14.29
Technology and computer science	37	5.87	20.16
Finance and banking	71	11.27	31.43
Education	84	13.33	44.76
Healthcare	53	8.41	53.17
Trade and services	171	27.14	80.32
Transport and logistics	28	4.44	84.76
Media and entertainment	21	3.33	88.10
Other	75	11.90	100.00
Total	630	100.00	

Table A5. Tabulation of position

	Freq.	Percent	Cum.
Office administrative employee	231	36.67	36.67
Specialist (e.g., marketing, finance, sales, etc.)	236	37.46	74.13
Director/Manager	44	6.98	81.11
Company owner	33	5.24	86.35
Other	86	13.65	100.00
Total	630	100.00	

Table A6. Tabulation of experience in a given position

	Freq.	Percent	Cum.
Less than a year	56	8.89	8.89
1-3 years	173	27.46	36.35
4-7 years	174	27.62	63.97
8-10 years	58	9.21	73.17
More than 10 years	169	26.83	100.00
Total	630	100.00	

Table A7. Tabulation of sector

	Freq.	Percent	Cum.
public	228	36.19	36.19
private	402	63.81	100.00
Total	630	100.00	

Table A8. Tabulation of AI using

Have you used AI before in your professional work or personal life?	Freq.	Percent	Cum.
Yes, at work	93	14.76	14.76
Yes, at work and in my personal life	141	22.38	37.14
I haven't used it, but I intend to use it	396	62.86	100.00
Total	630	100.00	

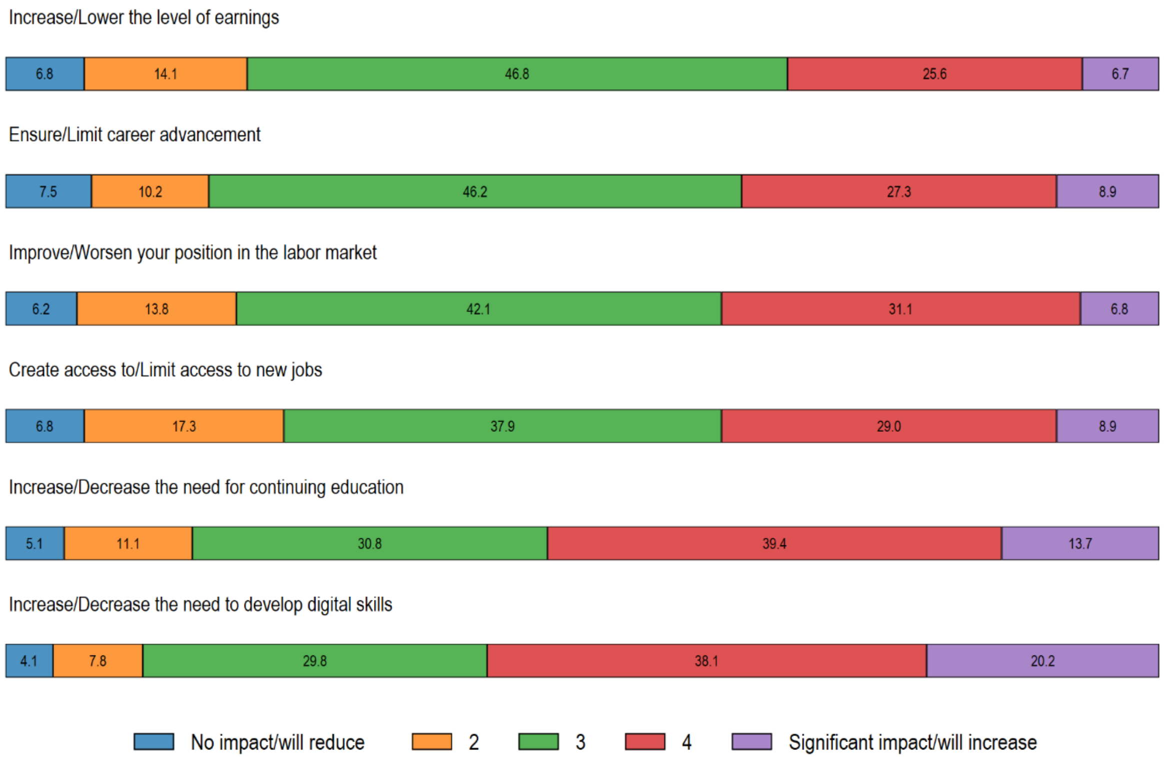

Figure A1. On a scale from 1 to 5, kindly rate your perception of how the use of AI may impact various aspects of your professional life (1 = No impact/will reduce, 5 = Significant impact/will increase)
Source: own elaboration.

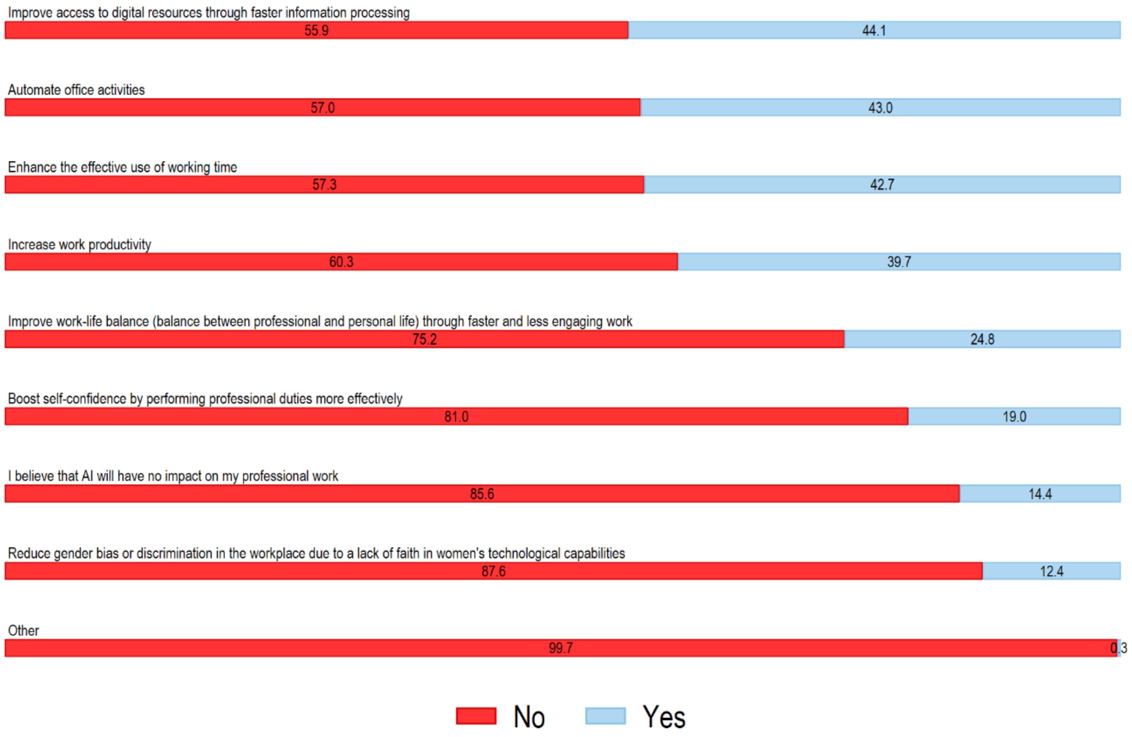

Figure A2. Please choose the areas in which you believe AI can assist you in your professional work
Source: own elaboration.

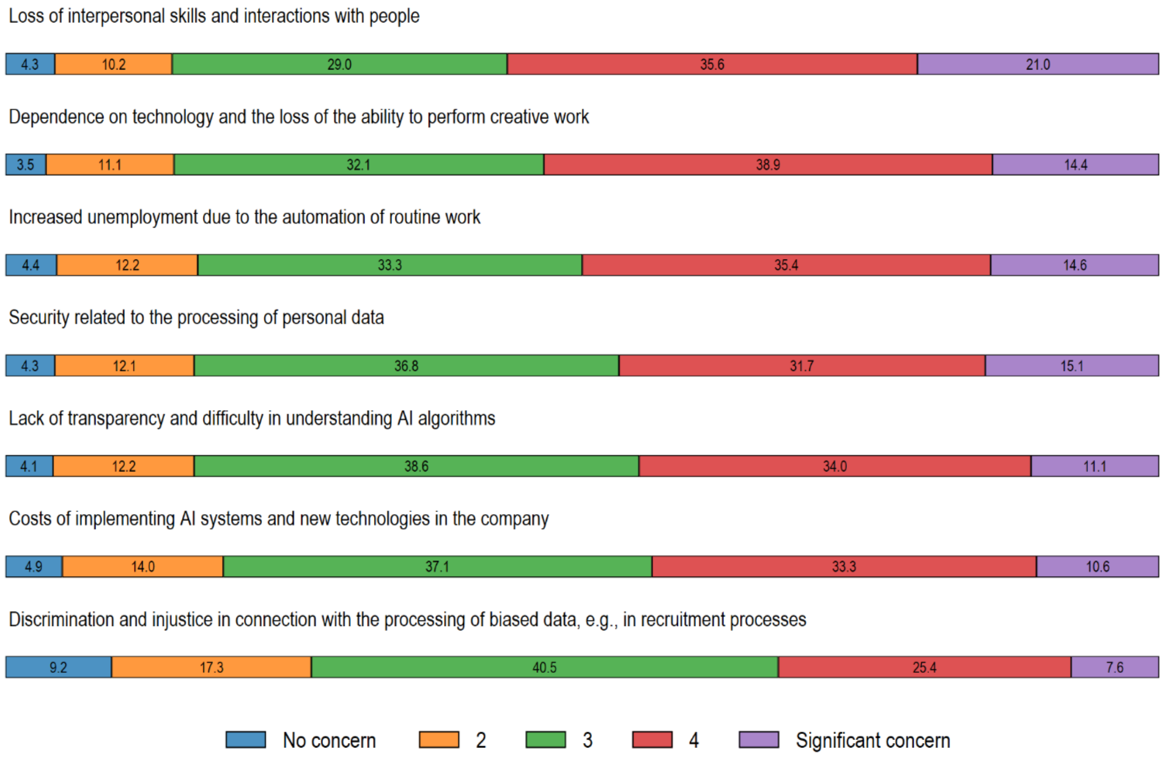

Figure A3. Please assess your concerns about the use of AI on a scale of 1 to 5 (1 = No concern, 5 = Significant concern)
Source: own elaboration.

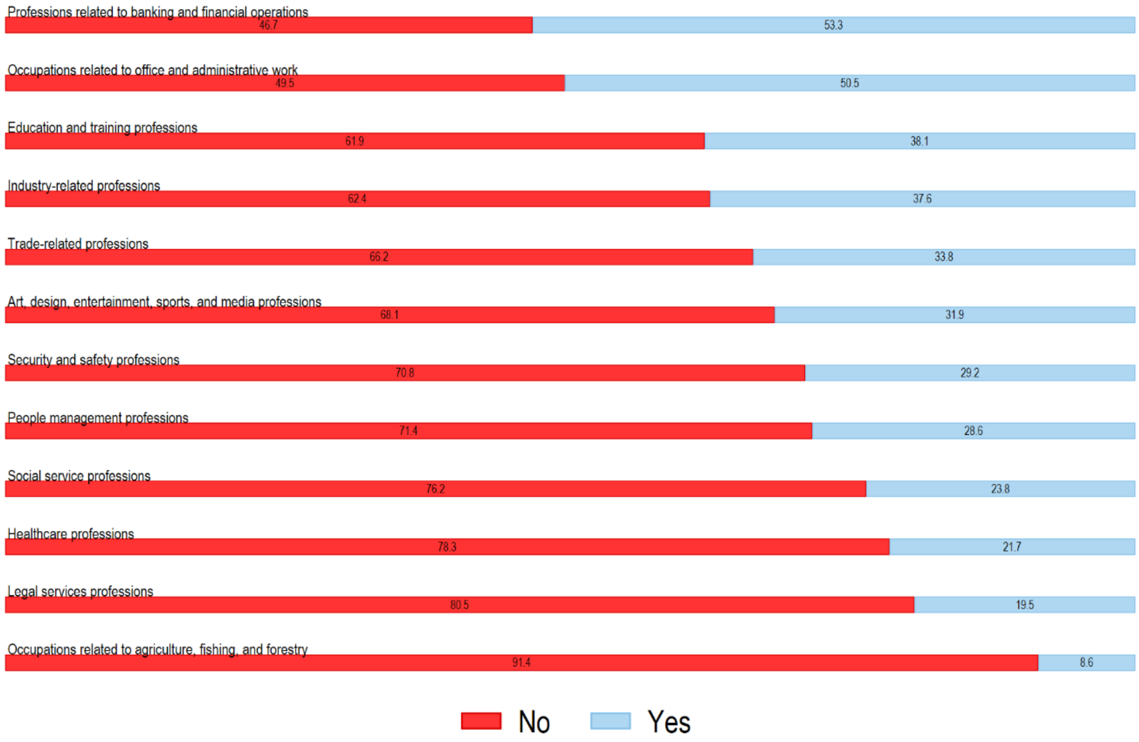

Figure A4. Please specify the professions where you believe AI is presently employed. You can select multiple options
Source: own elaboration.

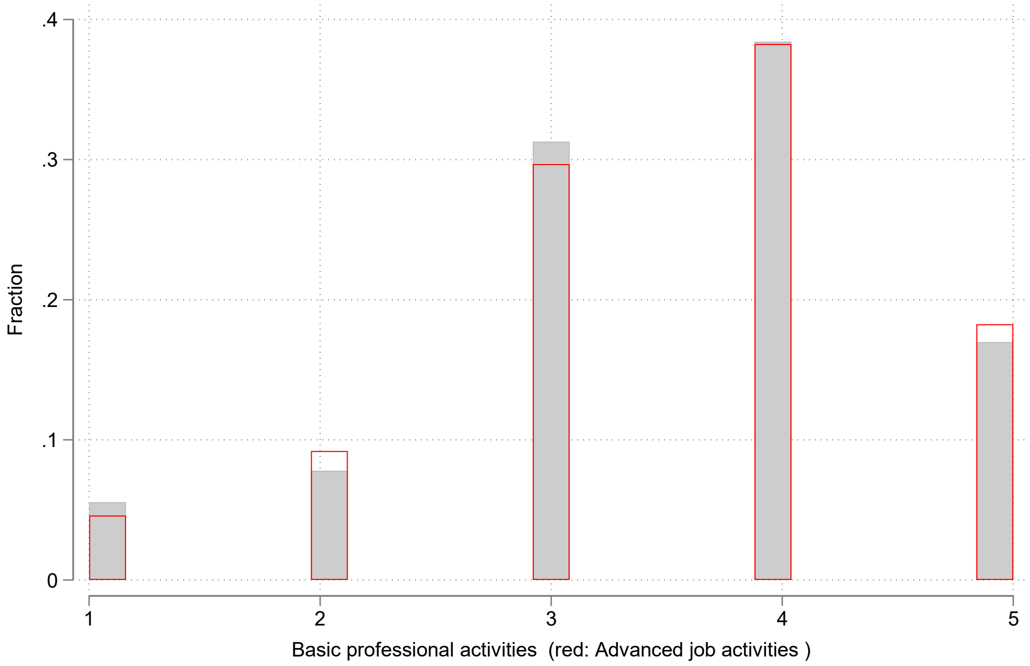

Figure A5. Please assess, on a scale from 1 to 5, where 1 signifies "Very low" and 5 signifies "Very high," the extent to which you incorporate AI into basic/advanced professional activities in your job.
Source: own elaboration.

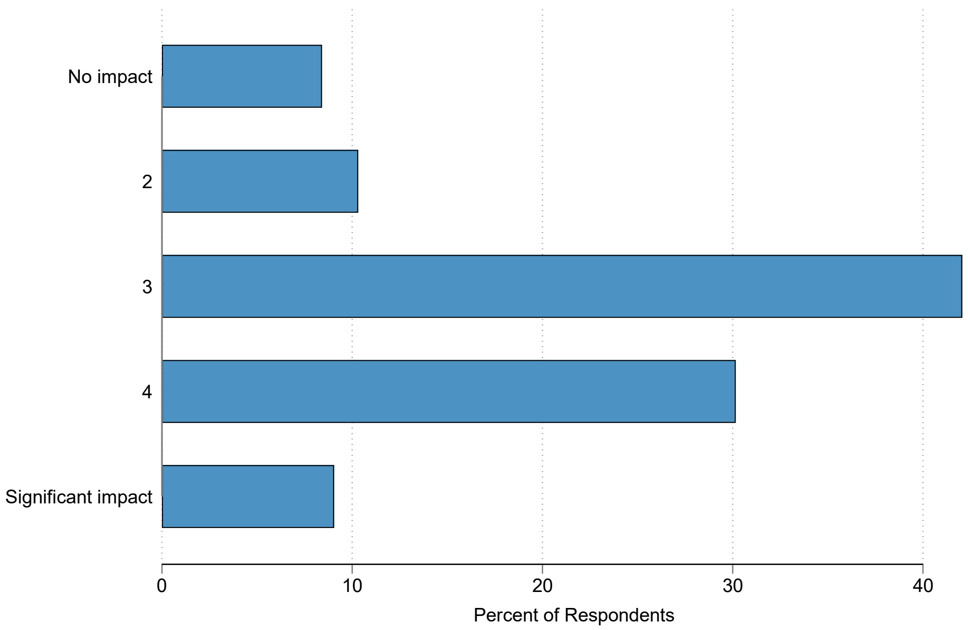

Figure A6. Please rate, on a scale of 1 to 5, how the utilization of AI influences your self-confidence in decision-making and problem-solving in your professional context
(1 = No impact, 5 = Significant impact)
Source: own elaboration.

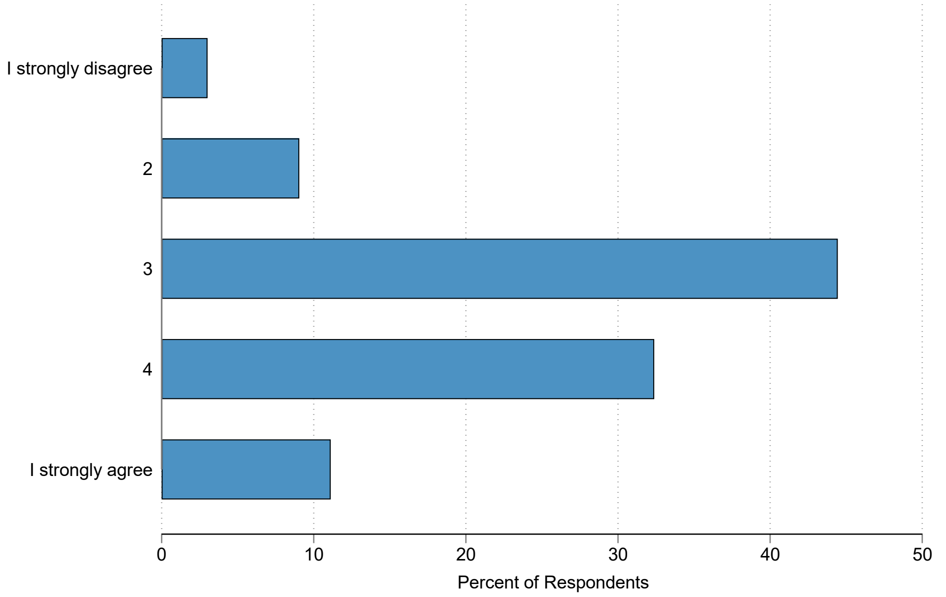

Figure A7. Indicate your level of acceptance of AI in your professional work on a scale of 1 to 5, where 1 signifies "I strongly disagree," and 5 signifies "I strongly agree"
Source: own elaboration.

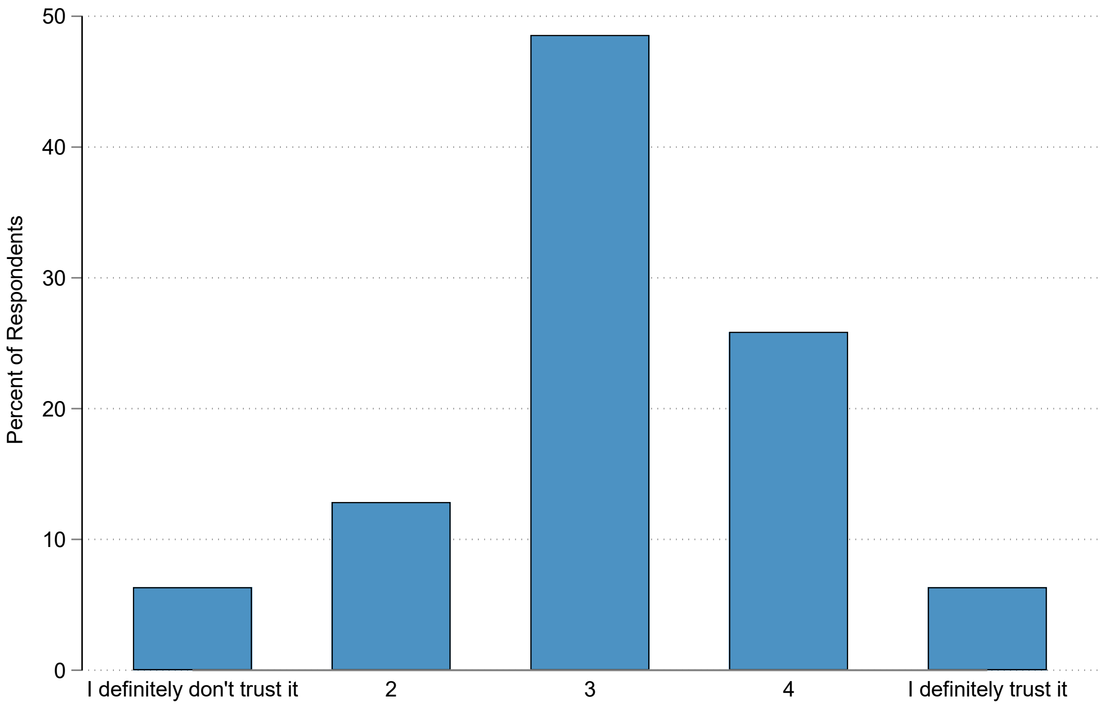

Figure A8. Rate your overall confidence in using AI in your professional work on a scale of 1 to 5, where 1 denotes "I definitely don't trust it," and 5 denotes "I definitely trust it."
Source: own elaboration.

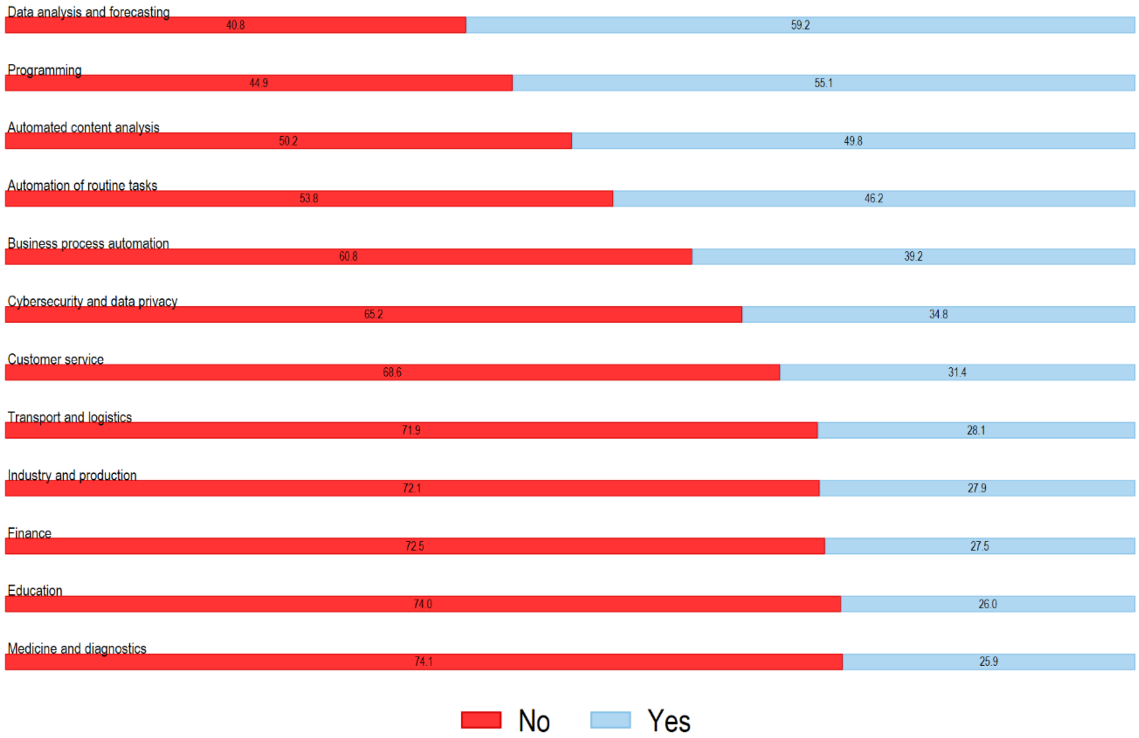

Figure A9. In envisioning the future, kindly specify the areas you deem most crucial for the application of AI. You can select multiple options
Source: own elaboration.

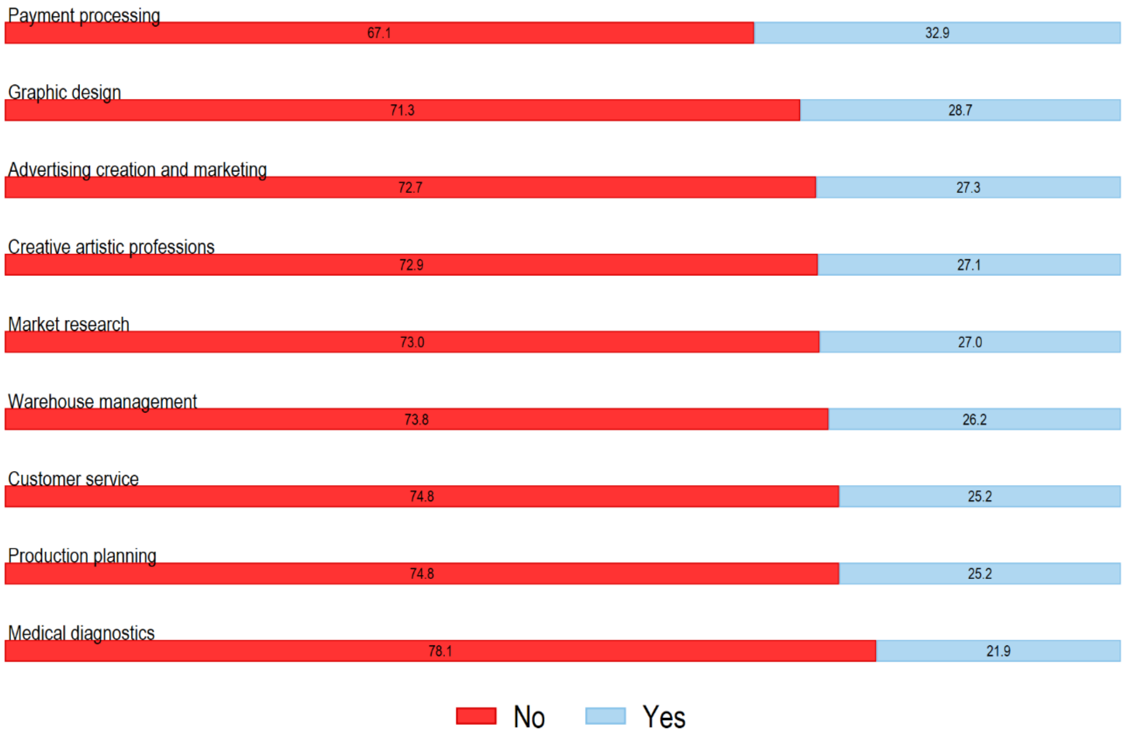

Figure A10. Select the areas where you believe developing digital skills is unnecessary, as you anticipate that AI algorithms will take over
Source: own elaboration.

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EXPERIMENTAL STUDIES OF ADVERTISING MESSAGE EFFECTIVENESS IN VIRTUAL REALITY

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Abstract: *One of the most important elements of advertising campaigns is their message. Many factors can influence message effectiveness,* inter alia*, the content, the form, the carrier, or the location of the advertisement. Together, these aspects can determine how visible the advertising message is to the audience. At the campaign-planning stage, it is usually hard to tell how the advertisement should be presented and properly exposed so that the recipients perceive and remember it. We propose performing the pre-test of advertisements with the use of a virtual reality system that provides the environment close to the natural conditions and using cognitive neuroscience tools to record the objective measures of the audience's opinions. Our proposal shows the procedure for designing and conducting an experiment that allows for an assessment of the advertising message effectiveness based on its visibility. The article also presents the preliminary results of a pilot experiment that was designed to test both the virtual reality system and the proposed procedure.*

Keywords: *Virtual reality, cognitive neuroscience tools, advertising messages, effectiveness.*

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INTRODUCTION

One of the most important elements of advertising campaigns is their message. The effectiveness of the campaign greatly depends on the extent to which its content reaches the recipients. The proper reception of the presented messages hinges on their form and content, as well as the manner and place of exposition. The most carefully designed and implemented message will not fulfill its role if it is not noticed by the audience. Therefore, knowledge about the reception of the message is extremely valuable to making decisions, already at the campaign-planning stage, regarding its presentation in such a way that the recipients can notice and remember it (Daszkiewicz, 2011).

The procedure for dealing with such a situation usually involves creating several possible variants of the message and pre-testing which variant is the most effective. For this purpose, various methods are used - most often questionnaires (Shukla, 2008): the message is shown to a group of subjects and a survey is conducted to collect their opinions, or structured interviews (Lincényi & Bulanda, 2023). However, survey methods do not provide knowledge that is reliable enough to choose the content or the way of displaying the message, because people sometimes cannot (or do not want to) determine their true preferences when asked about them (Calvert & Brammer, 2012; Zaltman, 2003). In addition, surveys are usually not conducted in an environment close to the natural conditions in which recipients come into contact with advertising messages.

Such problems could be solved with the use of virtual reality (with which you can create the impression of being in a natural environment) in combination with cognitive neuroscience methods that allow you to collect psychophysiological data and determine objective metrics defining the subconscious reactions and opinions of the subjects about the presented messages.

These methods include tools and techniques to measure, map, and record nervous system activity. They allow the observation of nervous processes taking place in real time. They fall into three broad categories: neuroscience tools and techniques that record neural activity (electromagnetic and metabolic) inside the brain (e.g., electroencephalography, magnetoencephalography, functional magnetic resonance imaging, near-infrared spectroscopy) and outside the brain (e.g., eye tracking electrocardiography, skin-galvanic reaction measurement, electromyography) and neuroscientific methods that allow the manipulation of neuronal activity (such as transcranial magnetic stimulation) (Lim, 2018). Mentioned methods are widely described in the literature (cf. (Bercea 2012; Kable 2011; Morin 2011; Plassmann et al. 2007; Ramsøy 2015; Żurawicki 2010)).

A virtual reality system using cognitive neuroscience methods can be a very helpful tool to support marketing decisions. On the basis of the data collected from the system, indexes (psychometrics) can be determined, which will help make decisions about the choice of a specific form and method of displaying the advertising message in terms of its effectiveness. For the purposes of this article, it is assumed that the effectiveness of the message can be assessed on the basis of its visibility for the recipients (more on the effectiveness of advertising in: (Wells, 2009)). Visibility is defined as the degree to which something is perceived by the public/audience (Cambridge Dictionary). It can be measured indirectly, including metrics such as attention (Dillard et al., 2007), recognition (Pashna et al., 2019), recall (Guixeres et al., 2017) or memorization (Vecchiato et al., 2014).

Due to the technological complexity of the proposed system, carrying out pre-tests of advertising messages in terms of their visibility to recipients is a very complicated process. Therefore, it is advisable to develop a detailed research procedure in this regard. The purpose of this study is therefore to determine such a course of experimental procedure that would allow the assessment of the visibility of advertising messages in various types of campaigns, at the planning stage, using a virtual reality system in conjunction with neuroscience methods. We also present the concept of virtual reality system that could be used to prepare an appropriate experimental environment. The article presents also the results of the pilot experiment that was designed to test the elaborated procedure and VR system.

VIRTUAL REALITY, ADVERTISING AND COGNITIVE NEUROSCIENCE – LITERATURE REVIEW

Virtual reality (VR) is understood as a computer-generated simulation of a situation involving a user who perceives it with one or more senses (mainly sight, hearing and touch) and interacts with it in a way that appears to be real (LaValle 2023; Parsons et al. 2017).
VR is a rapidly expanding topic, both in terms of technological advances and the domains of its applications – including experimental marketing research (Beck et al. 2019; Wei et al. 2019) or application in ecotourism (Folgado-Fernández et al., 2023). There is also a great interest in conducting such studies with simultaneous recording of the activity of the nervous system using various tools and methods of cognitive neuroscience (Russo et al., 2022), however, the question arises - does this research concern the use of a virtual reality system to pre-test various variants of the message at the stage of planning an advertising campaign?

For the purposes of this article, a literature review was made according to the procedure presented in Figure 1. The review focused mainly on academic literature relating to virtual reality, advertising and cognitive neuroscience. When selecting studies for the review the one of the largest multidisciplinary database was used – Scopus. The search was performed in February 2023.

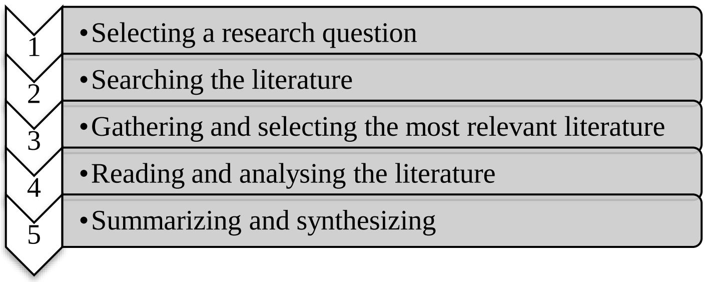
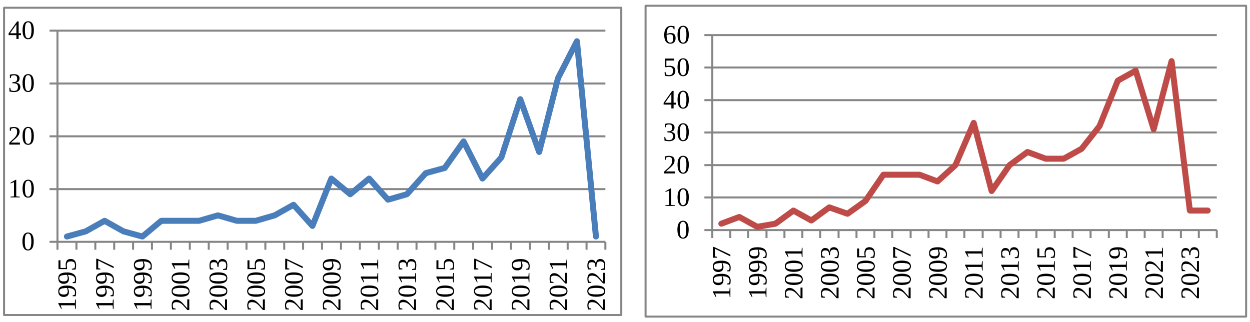


Figure 1. The literature review procedure

The search was performed with the use of basic combined keywords, relating to research question, as: (“virtual reality” OR VR), (advert* OR ads), (neuroscience OR psychometrics OR biometrics), (experiment*). Additionally, some general filters were applied to improve the search results for the aim of this study. These filters include: (1) search fields: keywords; (2) conference papers and articles; (3) papers written in English.

The search was conducted in two phases. The first uses the phrase: (("virtual reality" OR VR) AND (advert* OR ads)). 131 results were obtained. An analysis of the number of publications appearing from 1995 to 2023 confirms the growing - almost exponentially - interest in the use of VR in relation to advertising related research (Figure 2a). The obtained results were searched for the occurrence of the phrase (neuroscience OR psychometrics OR biometrics) - obtaining 16 publications, including 12 concerning experiments (experiment*).
In the second phase, the phrase: (("virtual reality" OR VR) AND (neuroscience OR psychometrics OR biometrics)) was used, obtaining 499 results. The number of publications appearing in the years 1997 - 2023 also confirms the growing trend in the interest in the use of VR in combination with neuroscience methods (Figure 2b). The obtained results were searched for the phrase (advert* OR ads) - obtaining 12 publications, including 9 concerning experiments (experiment*).



a b

Figure 2. The number of found publications in years

In total, 21 articles were received (12+9), of which 3 were repeated in both phases - thus 18 publications were then analyzed in the context of the research question. It turned out that (Hernández-Fernández et al., 2019) does not refer to VR, while (Russo et al., 2022) presents only theoretical considerations on the possibility of using VR and neurotechnics in marketing. As many as 7 publications found (Słupińska et al. 2021; Baumann and Sayette 2006; Mancini et al. 2021; Pozharliev et al. 2021; Ershow et al. 2011; Wang et al. 2019; Skeva et al. 2021) does not describe the use of VR in advertising, although one of them discusses experimental research in VR using cognitive neuroscience techniques (Słupińska et al. 2021).

The next 8 articles deal with VR as an advertising medium. Some of them present the results of experimental research - but conducted without the use of cognitive neuroscience methods (Griffin et al. 2023; Breves and Dodel 2021; Lo and Cheng 2020; De Gauquier et al. 2019). (Silberstein et al., 2020) presents theoretical considerations on researching VR as an advertising medium in conjunction with neuroscience methods, while (Grigorovici, 2001) considers the potential possibilities of VR as an advertising medium without connection with cognitive neuroscience. Very interesting from the point of view of our research question in this group of publications is the article (Leanza, 2017) presenting experimental study with the combined use of VR and registration of brain oscillations (delta, theta, alpha, beta) and skin conductance level, when subject observed four traditional TV commercials and four VR commercials. However, the purpose of the presented research was not to pre-test advertising messages, but to compare VR with another advertising medium in terms of effectiveness. Equally interesting is the article (Borawska et al., 2020) presenting the proposal of an experiment that allows to study the effectiveness of virtual reality game in raising awareness of healthy eating – but also applies to VR as an advertising medium.

Only one of the 18 articles selected for review refers to experimental research using VR and neuroscience in the context of pre-testing messages (on the example of a social campaign promoting safe driving) (Borawska et al., 2018), however, the focus is on the assumptions that meet the VR system to make such experiments possible, and not on the experiment procedure itself. This gap is filled by this article, which focuses on detailing the experimental procedure that allows for pre-testing various variants of the advertising message in both social and commercial campaigns.

EMPIRICAL RESEARCH PROCEDURE

Architecture of the Virtual Reality System

The architecture of virtual reality system used for conducting experimental research is presented in Figure 3. During the experiment, the examined persons will be controlling the object representing them in the simulation. This object could be a three-dimensional human model, but it is not required. In the real world, we see elements of our body, but if it is not important, our consciousness ignores them (like the nose). For this reason, the subject in our simulation is represented by an invisible stereoscopic camera and a pair of hands. The movement of the examined person's head is transferred to the movements of the camera, thanks to which the examined person can look around the simulation world as in the real world. In hands, the subject holds controllers whose movement is tracked, which allows for the appropriate placement of hand models in the simulation. The controllers are equipped with buttons and touchpads that allow performing various actions, such as opening the door. All actions performed by the examined person as well as the location of the camera and controllers are recorded for later analysis by the module for recording location, spatial orientation, collisions, and states.

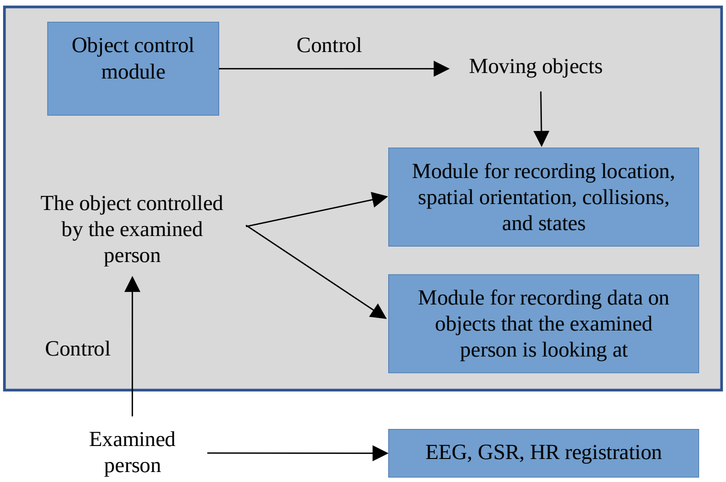


Figure 3. Architecture of VR system

In addition to the object representing the player, there are other objects in the simulation that can perform certain actions on their own. An example of such object could be a bus that moves around the city and has to halt at stops, taking care not to collide with other objects. The operation of these objects is managed by the object control module, which ensures their proper behavior by supervising their movement and reacting to unforeseen situations, such as the possibility of a collision with another object. The movements and actions of such objects are recorded by the module for recording location, spatial orientation, collisions, and states as well.

VR glasses are equipped with an eye-tracker, which allows you to check what the test person is looking at. The recording of data on such objects is handled by the module for recording data on objects that the examined person is observing. This module "fires" the beam in the direction the examined person is looking at and registers the name of the first object that the beam "hits". Such registration is made with the frequency of the eye-tracker, thanks to which, based on the number of noted object names, it is possible to calculate how long the examined person looked at a given object.

The tested person will have an EEG cap on and GSR and HR electrodes attached. EEG, GSR and HR data are synchronized with the simulation operation. This allows defining, for example, the emotions that are associated with performing certain activities in the simulation.

Course of the Experiment

The proposed course of the experiment was elaborated based on previous experience of the Authors concerning conducting the similar research and the literature review of publications relevant to the topic of the paper.

Proposed study can be realized according to the specified procedure that generally has two main stages – design and execution. In every stage certain steps should be performed to ensure the appropriate course of the research. The design of the experiment with its following steps is depicted in Figure 4. Where it is applicable next to the appropriate actions, corresponding methods and used tools are mentioned.

At the beginning of the procedure, the experimental design is prepared. At this stage all the factors considered to be relevant for the study are selected. The selection could include such elements as the format, the carrier and the location of advertising messages in the virtual environment. The next step is to choose variants of the messages which will be examined. Since they will be presented in three-dimensional environment at this stage also proper 3D scene will be prepared in order to ensure the right presentation of the stimuli. Then, the appropriate measurement methods (traditional or neuroscience) should be selected depending on the needs resulting from the nature of the tested product and the aspects that are of interest. In this phase also suitable metrics are chosen – depending on methods that are intended to be used. On the basis of the choices made at this stage, the number and characteristics of the tested people should also be determined and divided into appropriate subgroups in accordance with the considered variants of the tested materials. At the end of the preparatory stage, a detailed experiment scenario is developed, taking into account the method of presenting the materials to the test subjects. Depending on the nature of the research, in this step you should also formulate tasks to be performed by users, which will be carried out by them during the experiment.

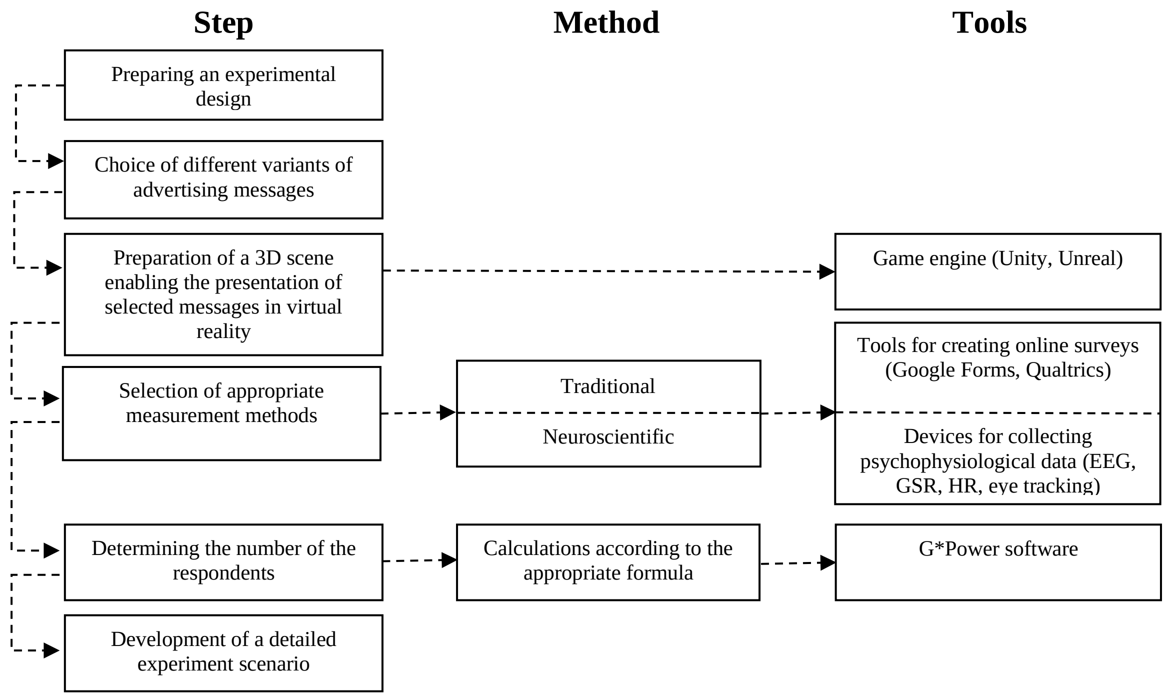


Figure 4. Design of the experiment

Once the study is designed, one can proceed to conduct the experiment (see Figure 5). It starts with the recruitment of participants. If it is needed for the purpose of the study, preliminary screening of the volunteers is conducted. It is done especially when the subjects need to fulfill certain conditions (e.g., have driving license or be familiar with VR technology). After the pool of the participants for the study is completed, each subject individually is invited to the research lab. In terms of time, it is advisable to choose the right hours to conduct the experiment. It is recognized that research should preferably take place between 9 and 11 am, due to the peak of cognitive abilities of participants (Babaç & Yüncü, 2022).

Before the exact experiment may begin, it is very important to perform proper preparation steps. First, the research laboratory room should have appropriately set and constantly monitored environmental parameters such as temperature and humidity. This is advisable in order to minimize their impact on the collected data (Liapis et al., 2021). Conducting the study should begin with familiarizing the subjects with the experimental environment and discussing the course of the study. After familiarizing themselves with the procedure, the examined person should give written consent to participate in the research project. If necessary, after giving consent, demographic and VR familiarity data is collected as well. The next step is the assembly and calibration of the VR googles and research equipment depending on the cognitive neuroscience methods selected for the study.

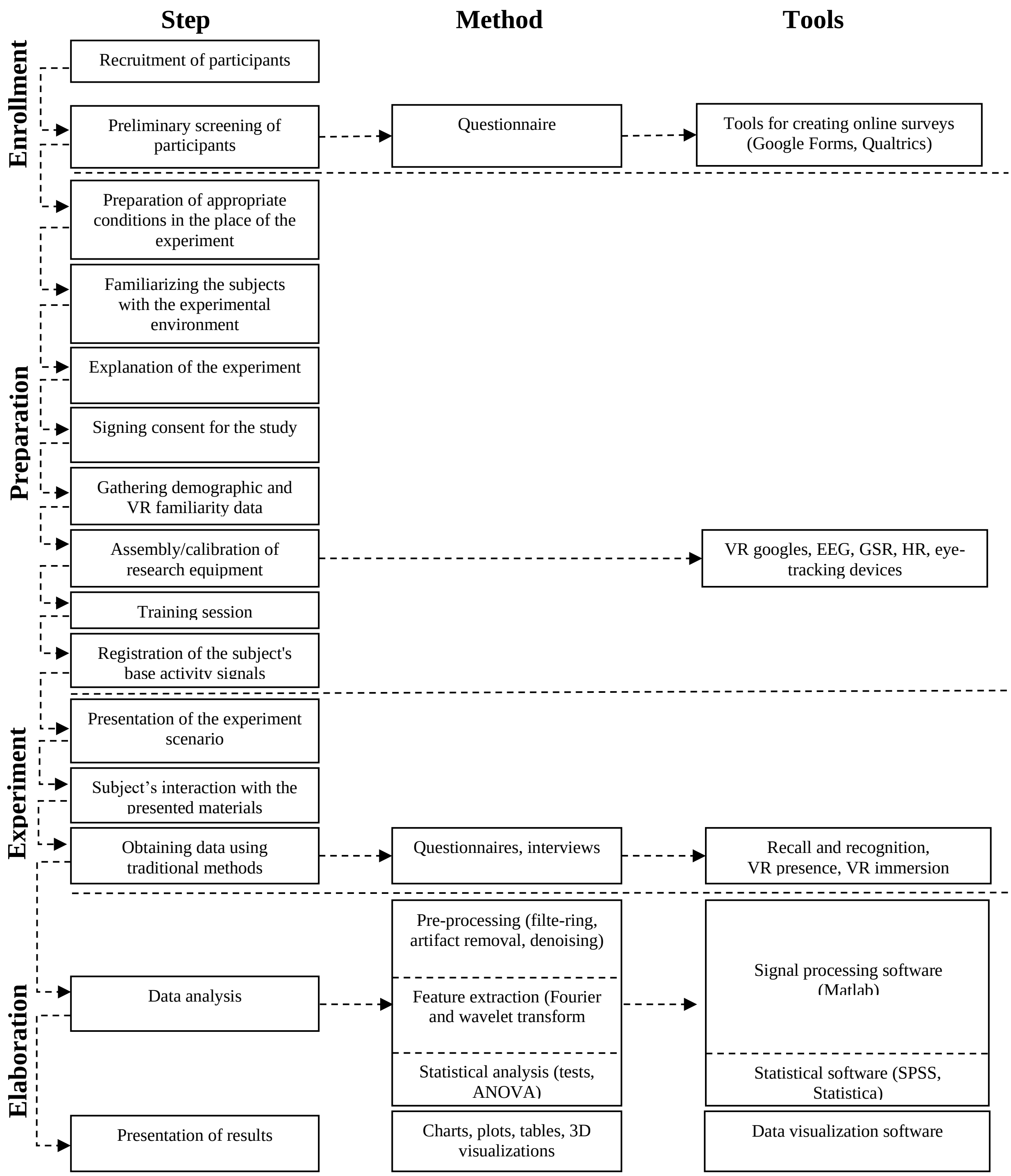


Figure 5. Execution of the experiment

At this stage, a training session is carried out to familiarize the subjects with navigation in the virtual environment and the requirements of the task (Riecke et al., 2002). Moreover, this step allows to exclude people who are not comfortable in the virtual environment (dizziness, headaches, fatigue and negative emotional activity such as anxiety and stress) (Kweon et al., 2018). After the start of the experiment, the measuring equipment records the base course of psychophysiological signals of the experiment participant at rest. In the further part of the study, the stimuli are presented, and the user performs tasks according to the scenario of the experiment. During the interaction with the presented materials, psychophysiological data is collected. The recorded signals can be supplemented with data from traditionally used research methods –interviews and questionnaires. Concerning the presented stimuli, it gives the opportunity to gather data about recognition and recall of given materials. Moreover, it allows to assess the immersion and presence of the subjects in the virtual reality using such tools as The Igroup Presence Questionnaire (IPQ) (Igroup, 2016). This stage ends the practical part of the study, followed by the analysis of the collected data, taking into account both subjective and objective measures. The procedure ends with the interpretation and presentation of the results.

PILOT EXPERIMENT TESTING THE VR SYSTEM AND PROCEDURE

Stimuli

Based on the described architecture we have created a virtual environment for the purpose of testing the visibility of advertisements. The main element of this environment was a model of a city in which participants should move following the certain path. Along the path, in three different places advertisiments concerning the energy saving were placed (see Figure 6). For the pilot experiment chosen places were: citylight next to the pedestrian crossing, billboard on the wall of one of the buildings and bus shelter. Apart of na object representing the examined person in the simulated environment we have put some other moving objects – cars and bus. They were used to enforce looking around while moving.
The advertisements used in the study come from the Polish social campaign of the Ministry of Climate and Environment – ”We save energy”[1]. They are still images and concern ways of saving electricity at home.

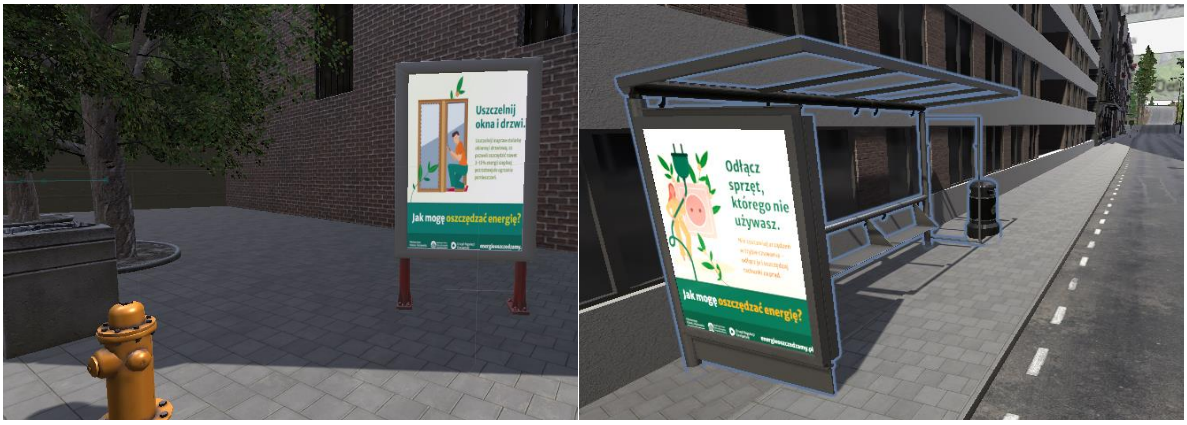


Figure 6. Screenshots of the virtual environment in the pilot experiment

[1] https://www.gov.pl/web/edukacja-ekologiczna/oszczedzamy-energie

Participants

The pilot experiment was conducted with 16 participants that are students of the University of Szczecin (including 11 males and 5 females). The sample size is comparable to other pilot studies described in the literature concerning eyetracking and virtual reality (Hummel et al., 2021; Kosmyna et al., 2021; Schröter & Mergenthaler, 2019; Vass et al., 2018). The subjects were between 18 and 24 years old. Most of them had previous experiences with virtual reality (75 %) but only 13 % use it on regular basis (once a week).

Procedure

The study was conducted at the Virtual Reality Laboratory at the Institute of Management at the University of Szczecin according to the procedure proposal presented in the article. The experiment took 15 minutes per one participant including the preparation and mounting the necessary equipment (VR goggles and eyetracker). After the training stage, the stimuli were presented. The scenario covered short walk through the streets of a virtual city along the route marked by arrows. The destination was a bus stop where the respondents were to wait for the bus. When the bus arrived at the stop, the experiment ended. In total, the time spent in the virtual environment did not exceed 5 minutes per participant. During the whole interaction with virtual environment, eyetracking data were collected. After completing the required tasks in VR, all participants filled questionnaire concerning their demographics, energy saving behaviors and immersion in virtual reality.

Data collection and processing

To perform the experiment the headset HTC VR VIVE Pro Eye was used. The resolution of the screen (Dual OLED 3.5" diagonal) of the device is 1440 x 1600 pixels per eye (2880 x 1600 pixels combined). The headset is equipped with an eyetracker (sampling rate 90 Hz). Analyses of the collected oculographic data was performed using Matlab software.

Measures

In the study we have gathered questionnaire and eye tracking data. Questionnaires included three main parts, apart of the demographic information. The first part was concerned with recall and assessment of given advertising materials. Next, there was a set of questions about the energy saving behaviors of participants and the frequency of performing these bahaviors. Each behavior was assessed on the Likert scale (1 – 5, where 1 was never and 5 always). The behaviors presented in this part to the participants are listed in the Table 2 in the results section.

The last part of the questionnaire allowed to assess the immersion and presence of the subjects in the virtual reality using The Igroup Presence Questionnaire (IPQ) (Igroup, 2016). This tool enables to measure the virtual reality experience of the participants along the four different dimensions – spatial presence, involvement, experienced realism and sense of "being there".

The eyeracking data were analysed in the context of areas of interest (AOI). In the virtual environment all three locations of advertising content was marked as AOI. Data recorded by eye tracker during the interactions of the participant with the virtual environment, after appropriate preprocessing give us the measure of gaze duration which is the total time spent looking at a particular area of interest.

Results

The spontaneuous recall of the presented advertising materials assessed by the questionnaire has shown that not all participant have paid attention to the advertising stimuli as they were focused on moving around in the virtual reality environment. Only one person in the study group has recalled the location of three advertising messages in VR environment. Two persons were able to point out two locations (bus stop and citylight) and nine remembered only a single spot (4 participants have noticed the advertisement on the bus stop, the same number paid attention to the billboard on the building wall and only one person in this group mentioned citylight). The rest of the group (4 persons) didn't pay any attention to advertising stimuli and didn't notice them in any location. Out of the 12 participants who have noticed advertisements, 7 of them remembered the topic of the campaign (58%).

The rest of the questions in the first part of the questionnaire was concerned with the subjective assessment of the presented advertisements and their locations. The detailed questions and the summary of obtained answers are presented in the Table 1.

Table 1. Subjective Assessment of Advertising Stimuli and their Locations in VR Environment.

Question	% of the whole group (16)		% of the group that noticed ads (12)	
	Yes	No	Yes	No
Do you think the social campaign content was appropriate for the selected ad location?	69	31	92	8
Were the ads clear and readable enough in virtual reality?	44	56	58	42
Do you think the social campaign was convincing and effective in conveying its energy saving message?	56	44	75	25
Did you like the advertisements of the social campaign about energy saving in the selected location?	62.5	37.5	83	17

The participants assessed the perceived effectiveness of the campaign, answering the question: *Rate the extent to which the ads you see would encourage you to save energy*. The Likert scale used for this evaluation was from 1 to 5, where the highest note indicated that campaign certainly will have impact on energy saving behavior of the participant. Taking into account the results of the subjects that actually noticed the advertisements and remembered the topic of the campaign the perceived effectiveness was assessed on average as 2.67 (SD = 1.07).

The next part of the questionnaire was intended to measure proenvironmental behaviors concerning energy saving. Participants were asked to determine their frequency of performing some of the most important actions aiming in energy conservation. The mean values and standard deviations based on their answers are presented in the Table 2. The three most common behaviors among the examined group include: switching off the lights in rooms that are not used, using natural light instead of artificial one when possible and limiting air conditioning and heating. The least frequent is using programmable thermostat (probably due to the investment that it requires), changing filters in cooling and heating systems and ironing in lower temperatures.

Table 2. Energy Saving Behaviors analysis.

Behavior	Mean	Standard deviation
I turn off the lights in rooms when not in use.	4.56	0.63
I unplug unused electronic devices from sockets.	2.50	0.63
I use a programmable thermostat to control the temperature in my home.	1.81	1.28
I change filters in heating and cooling systems according to the manufacturer's recommendations.	2.38	0.89
I save water when washing dishes and showering.	3.75	0.86
I try to use natural light during the day instead of artificial lighting.	4.19	0.91
I limit the use of air conditioning and heaters when they are not necessary.	4.00	0.73
I try to iron or dry clothes at lower temperatures to save energy.	2.44	0.89
I avoid leaving devices in standby mode.	3.13	1.09
I carefully insulate windows and doors to reduce heat or cooling loss.	3.25	1.44

To check the validity of virtual environment as a setting for pre-testing the advertising content, the last part of the questionnaire used IPQ scale (Igroup, 2016). The results obtained for the examined group are shown in Figure 7. The maximum possible value in each dimension could be 6. The virtual environment used in the experiment did not achieve that high results in any of the considered aspects. Best evaluation was achieved in the Spatial Presence dimension (M = 3.8, SD = 0.69) which is the sense of being physically present in the virtual environment. The subjective experience of realism was the weakest point of the presented VR environment (M = 1.89, SD = 0.87). The experience in VR was also assessed in the terms of physical well-being during the experiment. We have asked on question concerning the side-effects of virtual reality (dizziness, nausea). Three persons (all females) confirmed that they had such symptoms.

Figure 7. Radar chart showing the assessment of virtual environment experience along the four dimension

The eyetracking data registered during the experiment allowed to calculate how long each participant have looked at each advertising. The results are presented in the Table 3. Participants of our study did not pay any particular attention to any of the presented advertising stimuli. The most watched stimuli was presented on the billboard placed on the wall of one of the buildings, probably due to the size of the advertising and tha fact that it was visible from the distance. The second best location was bus shelter, since the participants were forced by the experiment scenario to remain near the bus stop for a longer period of time (waiting for the bus). Very little attention was given to the citylight placed near to the pedestrian crossing – the length of the total gaze on average was 0.13 (±0.22).

Table 3. Gaze duration depending on the location of advertisement

Advertisement location	Gaze duration (seconds)	
	Mean	Standard deviation
Citylight next to the pedestrian crossing	0.13	0.22
Billboard on the building's wall	0.82	1.09
Bus shelter	0.74	0.73

Discussion

The largest number of participant has noticed the advertising on the bus stop (7 out of 16 but only 5 of them rembered the topic of the campaign). This may be caused by the fact that their task was to wait for the bus in the bus shelter, so they have the opportunity and time to look at the ad which was placed there. The smallest number of subjects in the group paid attention to the citylight that was placed near to the pedestrian crossing. It may be due to the fact that they needed to look around when crossing the street in order not to be hit by a car. One of the persons that did not noticed any advertising had also pointed out in the free comment section of the questionnaire that the training session before the experiment was not sufficient in order to familiarize with the virtual environment and all attention was directed to navigation in the city and not to other elements of the environment. It is a strong indicator to lengthen the training session in performing similar experiments in the future.

Subjective assessment of the advertising stimuli and their locations in the virtual environment has shown that most of the participants had positive attitude towards the advertisement. The main problem was the clarity and readability of the campaign's message in the virtual environment. This could be the result of not sufficient resolution of the equipment (VR goggles screen). Taking this limitation into account we may state that for the time being the pre-tests of the advertisements in virtual reality should involve messages that do not contain much details and a lot of writings (especially small captions).

Issues with the clarity and readability could have affected the poor assessment of the perceived effectiveness of the campaign's message expressed by the participants. To confirm this conclusion, however, there should be an additional evaluation session of the advertising stimuli presented outside of the virtual environment. This could clarify if the advertisements are considered to be ineffective due to their content and the message conveyed or due to their imperfect virtual representation.

The survey concerning the energy saving behavior of the participants indicated that they are not fully aware of all the possible actions that can be taken in order to conserve the energy and they haven't implement them in their everyday life. The presented campaign was not able to convince them to change behaviors, as its perceived effectiveness was low. The main aspect of the research was, however, not to assess the effectiveness of the campaigns message itself, but evaluate the impact of the advertisement location on their visibility. Further experiments may include additional aspects of social advertising – in the context of energy saving it would be interesting, to check the environmental attitudes of the participants first, and then compare results in subjective and objective measures among the proenvironmental and nonenvironmental individuals.

The pilot experiment revealed that the virtual environment should be improved in order to increase its realism. Such improvements could enhance the quality of participants experience and increase the usefulness of virtual reality system as a tool of pre-testing the advertisements.

Concerning the problem of choosing best locations for placing advertising content, eye tracking data confirmed the results obtained with the help of questionnaires. The most remembered locations were building's wall (billboard) and the bus shelter and among all three advertising stimuli these two gained the most visual attention during the virtual tour. These results suggest that it is advisible to invest in large advertisements or put them in places were people are forced to spend more time outdoor. The location near to the pedestrian crossing did not meet expectations, since people were to busy looking whether it is safe to cross the street. Further research should take this result into account. It could be advisable to test if the presence of traffic lights on the pedestrian crossing could improve the visibility of the advertising, as they provide a reason for people to stop and take the responsibility off pedestrians to ensure they can cross the street safely.

CONCLUSION

The aim of the article was to propose the research procedure for designing and conducting experiments with the use of virtual reality system and cognitive neuroscience techniques to assess the effectiveness of advertising message in terms of its visibility. The focus was on presenting the advised course of a study and the features of a system that allows to create experimental environment using virtual reality. The proposal presented in the article was tested by performing a pilot experiment. It has shown that it can be a very interesting and promising approach to test the effectiveness of advertising messages before they are aired to the public. However, there are some limitations of this proposal that need to be considered. During the experiments conducted in the virtual reality we may encounter the issue of simulator sickness (Kweon et al., 2018) experienced by some participants. It may exclude them from participation in the study. Additionally, there is a challenge in creating the virtual environment itself to provide high levels of presence and immersion that correspond to reality. Despite of these concerns we believe that the proposed approach can bring substantial benefits for the advertising message effectiveness assessment. The next steps of our research assume performing more experiments with the greater pool of participants in order to introduce the refinement of the procedure and the VR system to suit better the purposes of pre-testing advertising messages of commercial and social campaigns aired in Poland

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AUTOMATIC ANALYSIS OF X (TWITTER) DATA FOR SUPPORTING DEPRESSION DIAGNOSIS

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Abstract: *Depression is an increasingly common problem that often goes undiagnosed. The aim of this paper was to determine whether an analysis of tweets can serve as a proxy for assessing depression levels in the society. The work considered keyword-based sentiment analysis, which was enhanced to exclude informational tweets about depression or about recovery. The results demonstrated the words used in the posts most often and the emotional polarity of the tweets. A schedule of user activity was mapped out and trends related to daily activity of users were analyzed. It was observed that the identified X (Twitter) activity related to depression corresponded well with reports on persons with depression and statistics related to suicidal deaths. Therefore, it could be construed that people with undiagnosed depression express their feelings in social media more often, looking, in this way, for help with their emotional problems.*

Keywords: *Twitter (X), tweet analysis, depression, data cleaning, data analysis.*

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INTRODUCTION

According to the World Health Organization (WHO), depression is the most common illness worldwide and the leading cause of disability. Over 260 million people worldwide suffer from depression, and over 800,000 people lose their lives every year due to suicides. It has been found that untreated depression is the main reason of suicides among teenagers, and suicides are the second leading cause of death in people aged 15-29 (WHO, 2017).

Mild symptoms of depression, which are often ignored, should not be neglected as very often they are harbingers of much more serious problems. The latter sometimes require hospitalization or even lead to attempted suicides (Halfin, 2007). Moreover, early diagnosis of depression is crucial as psychosocial treatment is especially effective in cases of mild depression. Unfortunately, over 50% of people suffering from this disease are undiagnosed. The lack of resources, lack of trained health care workers, and social stigmatization associated with mental disorders are the main barriers to effective care.

In 2020, the problem of depression worsened as the COVID-19 pandemic started. Multiple studies have shown that the lockdown related to COVID-19 has significantly impacted not only the economic and social aspects of peoples' life, but also the mental health of many. It was found that the rates of depression, anxiety, posttraumatic stress disorder (PTSD), and stress symptoms greatly increased during COVID-19 in comparison to earlier statistics, especially among females, youths, and low education groups (Xiong et al., 2020).

The widely accepted methods of treatment for medium and severe depression include psychology therapies (Cognitive Behavioral Therapy – CBT or Interpersonal Therapy – IPT) and medicines (selective serotonin reuptake inhibitors – SSRIs or tricyclic antidepressants – TCAs). While it has been found that after six months of treatment, the remission rate of depression is higher than 65% (Sinyor, Schaffer, & Levitt, 2010), over 50% of people suffering from this disease remain undiagnosed despite these ways of depression treatment. Current methods of identification, support, and treatment of clinical depression are considered ineffective, however, there is a greater need to improve the techniques of identifying depression rather than the methods of its treatment.

At present, many scientific institutions are investigating modern methods of identifying depression; it was hypothesized that depression could be identified from analyzing posts made on social media, with reliable statistical results. People with mental health disorders face stigmatization, and often prefer to talk about their problems through social networking sites rather than with their relatives or friends.

The aim of this research was to investigate whether it was possible to support a diagnosis of depression gleaned from automatic analysis of data, obtained from social networks, namely Twitter. Behavioral patterns regarding the activity of Twitter users related to depression and suicidal ideation were found and analyzed.

SOCIAL MEDIA

Social media allow users to create online content, exchange information, share their ideas or interests. Availability of mobile communication all over the world, as well as the increase of worldwide use of the Internet influences significantly the number of users of social media.

Currently over 45% of the world population belong to virtual communities and networks (Islam et al., 2018; Bachrach et al., 2012). According to data collected by Data Reportal (datareportal.com), BankMyCell (bankmycell.com) and Statcounter (gs.statcounter.com) there are 4.48 billion social media users worldwide, and this number increased over two-fold since 2015. The increase of the number of social media users since 2015 is presented in Figure 1 (Dean, 2022).

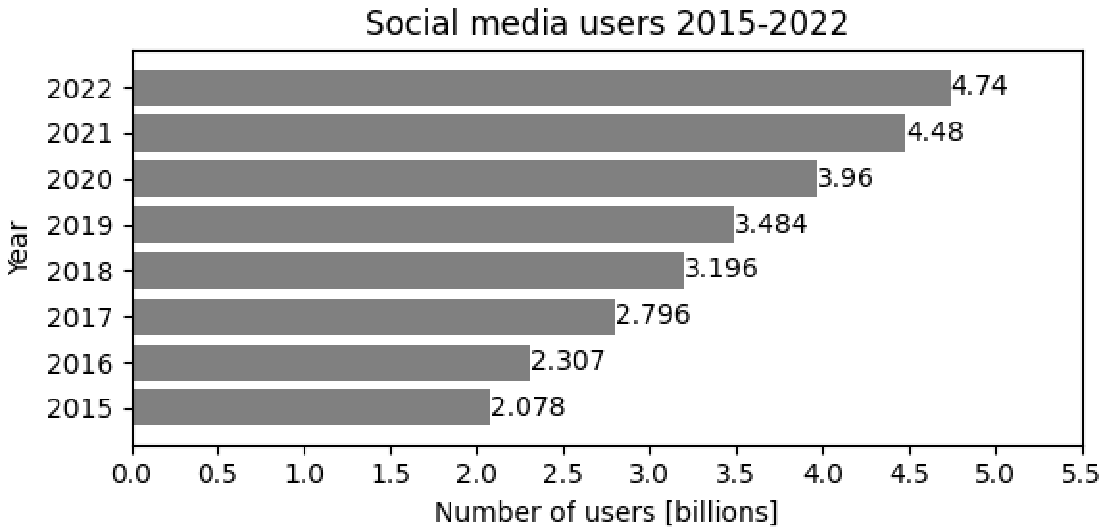

Figure 1. Number of social media users (2015-2022)

Among most often used social media are Facebook, Instagram and Twitter. The number of users of main social media is presented in Figure 2 (Dixon, Jul 26, 2022).

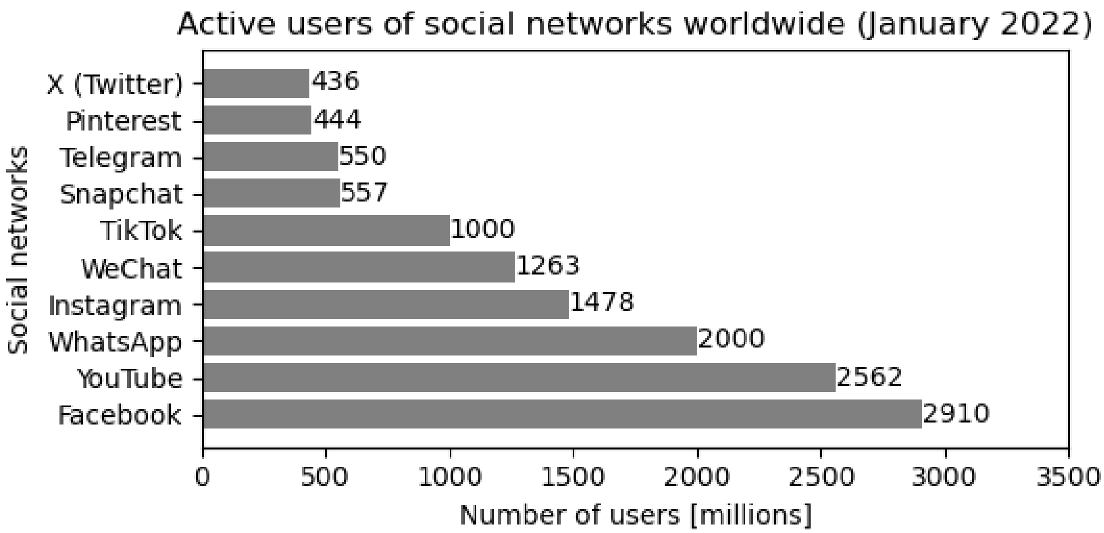

Figure 2. Use of social media in 2022

In recent years the number of people using platforms such as Facebook, X (Twitter) or Instagram to express their opinions, talk about their feelings and share their experiences have been increasing with every year. This makes social media platforms valuable resources to collect data about the society, including the state of publics' mental health (Mitchell, Hollingshead, & Coppersmith, 2015; Preoţiuc-Pietro et al., 2015; Conway, & O'Connor, 2016; Ernala et al., 2018; Mazuz, & Yom-Tov, 2020).

Platform X, formerly known as Twitter, is one of the social media platforms that allows for 'microblogging'; registered users may send or answer to so called 'tweets' – short text messages up to 280 characters, displayed on their public profile and visible to other accounts observing that profile. Twitter also allows for 'tagging' keywords or phrases by making use of so called 'hashtags' (# sign before the word or phrase). Users can write short messages on their profiles via direct website interface, SMS or mobile applications. Twitter is also a very popular means of communication amongst celebrities, politicians, businesses, diplomats and journalists to name a few. At present, most of public institutions, corporations, journals, and other organizations maintain official Twitter profiles as part of their online presence. Twitter users may read posts of persons with similar interests or similar problems, whilst at the same time maintaining a degree of anonymity.

The number of Twitter users accounts reported in 2022 was equal to 396.5 million what accounts for 8.85% of the worldwide social media users. The growth in the number of users is presented in Figure 3 (Dixon, Oct 6, 2022) and the distribution of Twitter users worldwide by age group (April 2021) is shown in Figure 4 (Dixon, Mar 29, 2022).

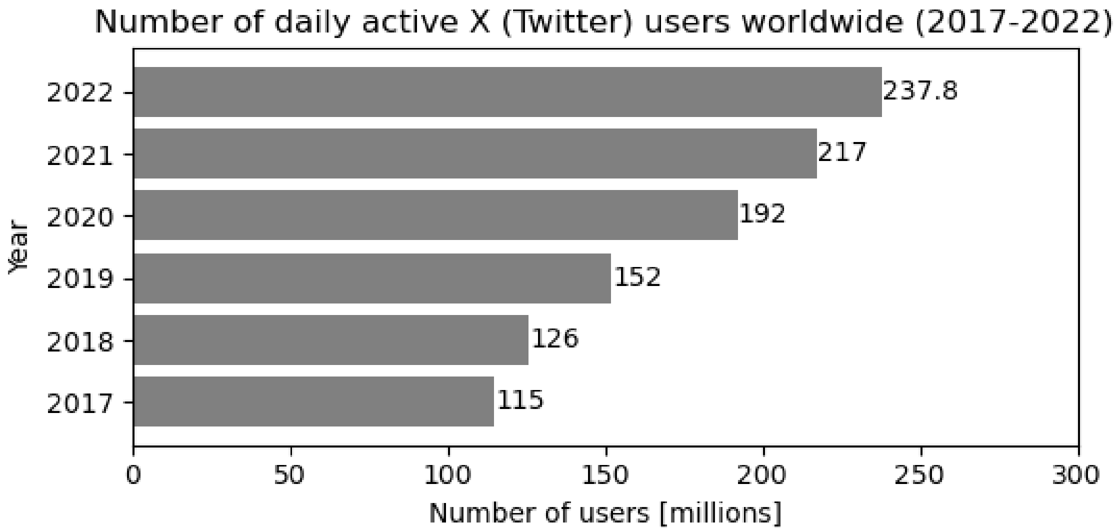

Figure 3. Increase in the number of X (Twitter) users in years 2017-2022

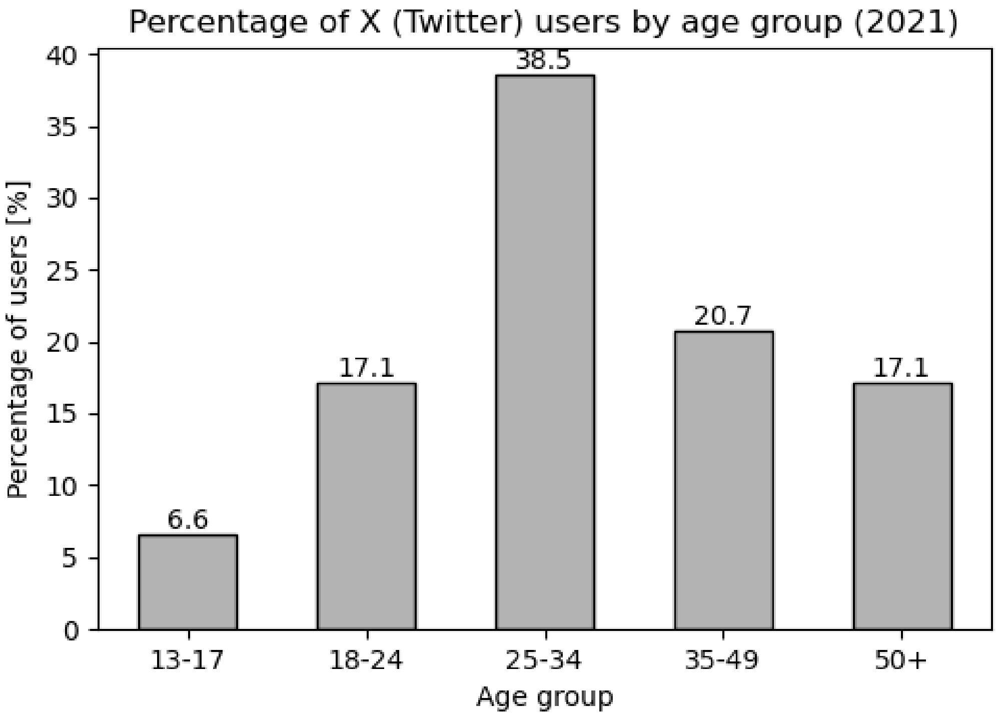

Figure 4. Distribution of X (Twitter) users by age groups

The ability of social media users to maintain anonymity makes such people more willing to share their problems with others without fear of stigmatization or other 'real world' repercussions. Such problems can include otherwise private physical and mental health disorders including depression. This observation suggests that Twitter can potentially provide a useful tool for surreptitiously observing social trends and data collected.

DEPRESSION

According to Oxford dictionary definition depression is "a medical condition in which a person feels very sad, anxious and without hope and often has physical symptoms such as being unable to sleep." (Oxford University Press, 2022). Nowadays depression, also known as major depressive disorder, is a common problem all over the world. According to World Health Organization (WHO) over 264 million persons worldwide suffers from this disease (WHO, 2017), which is considered as the fourth most serious health problem. Around 800000 people each year commit suicide. It has been found that not treated depression is the main reason of suicides among teenagers (Mann et al., 2005). The statistics showing the increase in terms of depression rates from 2017 to 2022 worldwide, in European countries and in USA are presented in Figures 5-7 (Alltucker, & Price, 2018; Dattani, Ritchie, & Roser, 2022; Depression Rates by Country, 2022; Depression Rates by State, 2022).

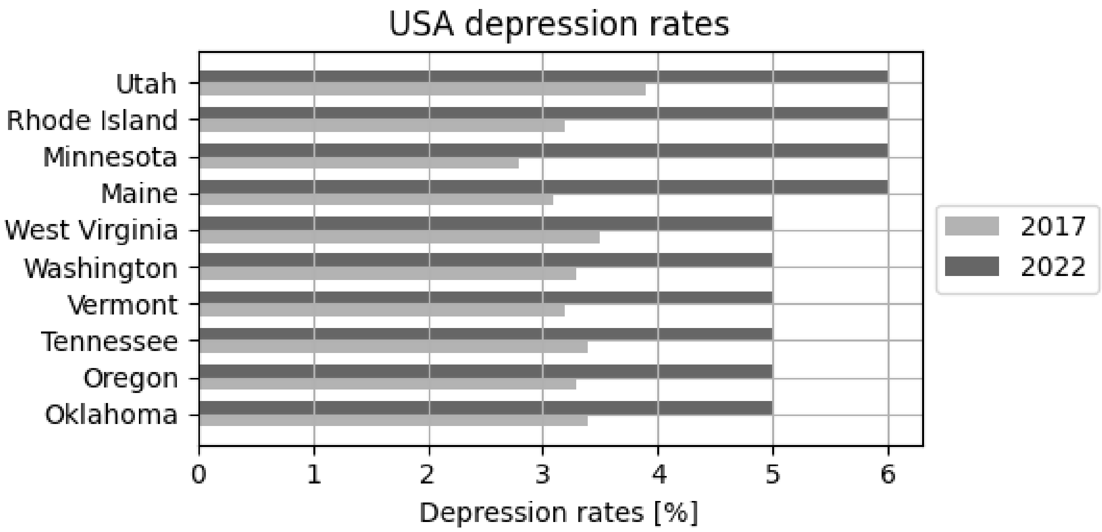

Figure 5. Comparison of depression rates in USA between years 2017 and 2022

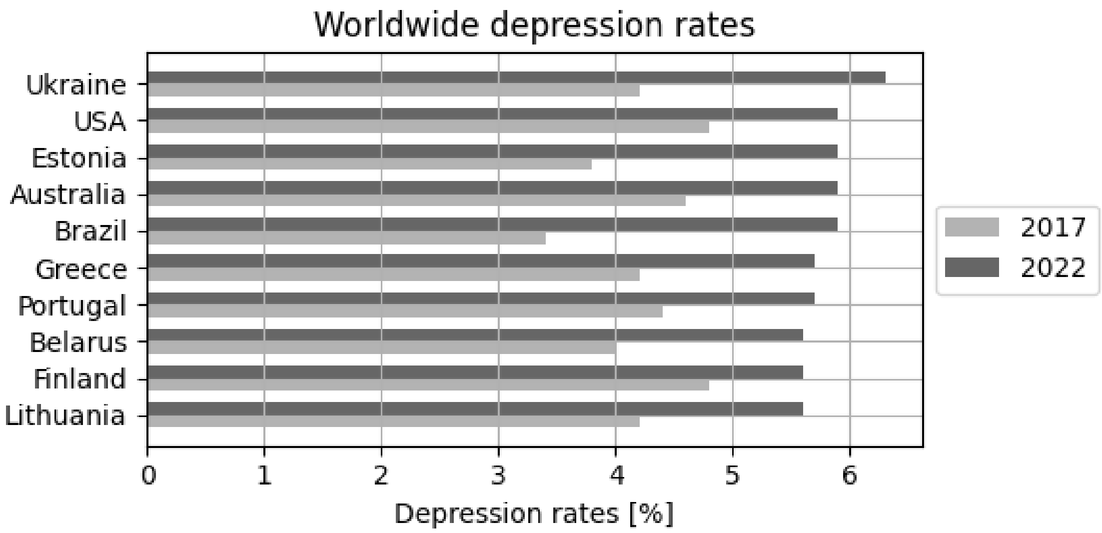

Figure 6. Comparison of depression rates worldwide between years 2017 and 2022

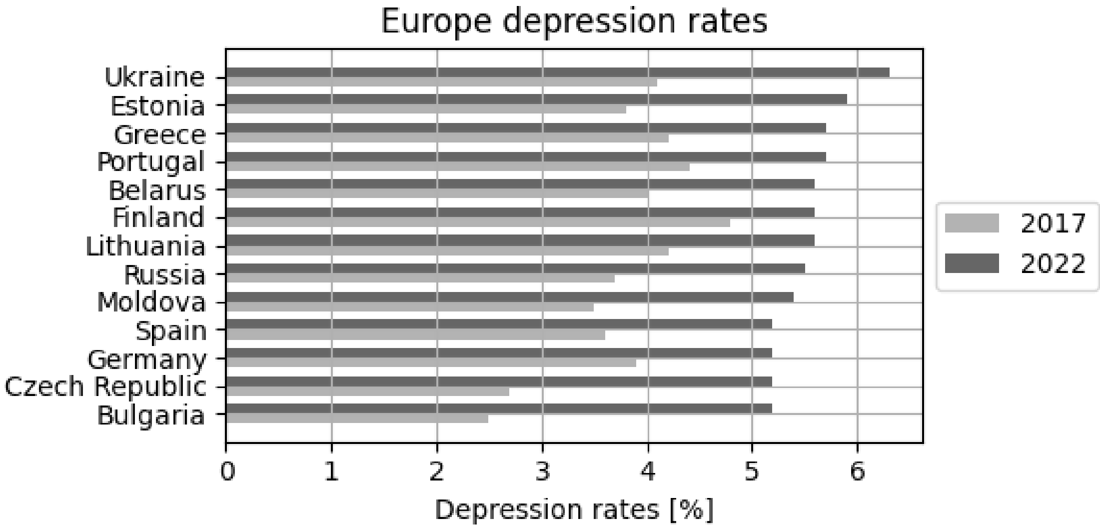

Figure 7. Comparison of depression rates in Europe between years 2017 and 2022

Depression can be classified into three categories depending on the number and severity of symptoms: mild, moderate or severe. Symptoms of depression include emotional ones, like feeling of sadness or loss of interest in activities once enjoyed, but also physical, such as headache, aching muscles and joints, gastric problems or decreased vision. There are several methods for self-diagnosis of depression, such as Beck Depression Inventory BDI (Beck, Steer & Brown, 1996), Center for Epidemiologic Studies Depression Scale CES-D (Radloff, 1977), Patient Health Questionnaire – 9 PHQ-9 (Kroenke, Spitzer & Wiliams, 2001) and Geriatric Depression Scale GDS (Yesavage et al., 1982). The most widely used diagnostic evaluation tools are DMS-5 (American Psychiatric Association, 2015) and ICD-10 (WHO, 1993). DSM-5 defines 9 criteria of depression: (1) depressed mood, (2) diminished interest or pleasure, (3) significant changes in appetite or weight, (4) insomnia or hypersomnia, (5) psychomotor agitation or retardation, (6) fatigue or loss of energy, (7) feelings of worthlessness and guilt, (8) diminished ability to concentrate, and (9) recurrent thoughts of death or suicide. ICD-10 scale is very similar to DMS-5 but gives the possibility to assess the severity of depression depending on the number of symptoms. However, it is common to misdiagnose depression (Eichstaedt et al., 2018; Dedovic, & Ngiam, 2015).

Since 2020 we can observe increase of the cases of mental illness, including depression, related to COVID-19 pandemic (Li et al., 2020; Liu et al., 2020). Most often appearing problems are the increased despair or anxiety, feeling of guilt, posttraumatic stress disorder (PTSD), but also insomnia, larger alcohol and drug consumption or increase in smoking (Li et al., 2020; Xiong et al., 2020).

A number of studies has been conducted in various countries all over the world to evaluate the prevalence of depression and generalized anxiety disorder (GAD) during the COVID-19 pandemic. Research done in Ireland showed that 20% of examined sample of 1041 Irish representatives suffered from GAD and 22.8% were diagnosed positively for depression (Hyland et al., 2020). In Hong Kong study a group of 500 respondents was questioned, out of which 19% reported depression, 14% reported anxiety and 25.4% reported deterioration of mental health since pandemic (Choi, Hui, & Wan, 2020). Study conducted in the US showed that the prevalence of depression symptoms in the USA was more than 3-fold higher during COVID-19 compared with the numbers collected before the COVID-19 pandemic (Flegal, Graubard, Williamson, & Gail, 2007).

It has been found that people with depression very frequently use social media (Neira & Barber, 2014; Lin et al., 2016; Rasmussen et al., 2020). Among social media users with depression changes in social relationships, activity and language were observed (DeChoudry, Counts, & Horvitz, 2013, April; Zulkarnain, Basiron & Abdullah, 2020). The main linguistic markers of depression are the focus on oneself and using first person singular pronouns (Chung & Pennebaker, 2007; Mowery et al., 2017; Preotiuc-Pietro et al., 2015), using words related to negative emotions, associated with depression anxiety and illness (Nguyen et al., 2014; Jung, Park & Song, 2017; Guntuku et al., 2017), as well as frequent use of absolute words such as “always”, “never”, “entire” (Al-Mosaiwi & Johnstone, 2018).

PRIOR AND RELATED RESEARCH

In countries with high income levels, people with depression are often not properly diagnosed, and others who do not have such a disorder are too often misdiagnosed and are prescribed antidepressants. In addition, in Western societies it is believed that a well-mannered person should be able to control his or her emotions, including depression, and it is believed that a person should be able to cope with depression.

Often, people who notice the symptoms of depression in themselves, are ashamed to admit to their relatives or tell the doctor about it. In this case, there is a chance that such a person, especially young, wanting to vent their emotions will use social media to anonymously talk about his or her problems and find people who would show understanding. During the annual meeting of the Association of Psychological Sciences in San Francisco (Rettner, 2018), the results of research conducted on over 500 students were presented, which showed that people with symptoms of depression described themselves as heavily dependent on social media, much more often than people without any symptoms, and they had often very active Twitter accounts with over 300 people watching them.

Another study, conducted between 2009 and 2010 with a group of students at the University of Wisconsin-Madison, showed that over thirty percent of those identified as having a depression according to the PHQ-9 scale that participated in the study, showed symptoms of depression in Facebook posts (Moreno, Christakis, Egan, Jelenchick, Cox, Young, Villiard, & Becker, 2012). The aim of this study was to identify the links between the visible symptoms of depression on Facebook and the symptoms of depression reported by them during the clinical trial. Public Facebook profiles of students from two universities have been checked for shared references regarding depression. Profiles have been classified as indicating symptoms of depression or not indicating the symptoms of depression. Participants completed an online survey that allowed to determine the scale of depression according to PHQ-9. The analyzes examined the relationship between the result of the questionnaire and the indicators of depression symptoms for people showing and not showing symptoms of depression. The mean PHQ-9 score for people without any symptoms was 4.7 (SD = 4.0), the mean PHQ-9 score for depressive symptoms was 6.4 (SD = 5.1, p = 0.018).

Since it was noticed that there is a correlation between depression and the content of posts made available by people with depression through social networking sites, the researchers began to work on the possibilities of using social media to diagnose depression. Social media content from platforms provide a lot of information about the users' moods, feelings, and behaviors. This data reflect people's mental health in their everyday life. Therefore Geographic Information System (GIS) and social media data mining are more and more often used tools enabling investigation of the spatiotemporal pattern of mental stress (Jahanbin, & Rahmanian, 2020; Coppersmith, Dredze, & Harman, 2014; De Choudhury, Counts, & Horvitz, 2013 May).

Automatic analysis of posts from social networking sites potentially provides methods for early detection of depression. If an automated process could detect elevated depression symptoms in a user, the person could be directed to a more in-depth assessment and to be provided with further support and treatment (Guntuku et al., 2017).

Platforms most often used in data mining and analysis for depression detection are Facebook (Islam et al., 2018; Eichstaedt et al., 2018), Twitter (De Choudhuryet al., 2013 April; Collingwood, 2016; Tadesse, Lin, Xu, & Yang, 2020; Reece et al., 2017) and Reddit (Tadesse, Lin, Xu, & Yang, 2019; Cacheda et al., 2019). Results from the analysis of Facebook data show accuracy of depression detection at the level of 60-70% (Islam et al., 2018; Eichstaedt et al., 2018). Study combining data from Facebook and Twitter for depression detection reported similar values, namely 57% accuracy, 67% precision and 56% recall (Aldarwish, & Ahmad, 2017). Much better results were reported for analysis of Twitter posts showing the accuracy from 70% using crowdsourcing (De Choudhury et al., 2013 May), 85% accuracy with combination of Naive Bayes classification and Multiple Social Networking Learning (Collingwood, 2016; Reece et al., 2017) to 91.7% accuracy of the algorithm based on Principal Component Analysis and Support Vector Machine 10-fold cross validation (Tadesse et al., 2020). A number of papers report the use of sentiment and emotional analysis on Twitter data (Coppersmithet al., 2014; De Choudhury et al., 2013 April; Go, Bhayani, & Huang, 2009; Zhou, Tao, Yong, & Yang, 2013). It was found that the use of sentiment analysis, along with percentage of depressed tweets, increases the precision and recall of detecting depression (Jamil et al., 2017). De Choudhury et al. (April 2013) and Jamil et al. (2017) extracted features from the tweets of people with depression to increase the detection accuracy of algorithms using sentiment analysis. DeChoudhury (April 2013) built a depression lexicon of terms that are likely to appear in posts of persons talking about depression. Jamil et al. (2017) used the percentage of depressed tweets and the information about the self-indication with depression of the tweet author in order to include or delete such user from the training set, what increased the detection accuracy. Detecting depression from Spanish tweets using sentiment and emotion lexicons was also used by Leis et al. (Leis et al., 2019).

Early studies on depression detection by tweets analysis used relatively small data samples, with less than 500 users. Coppersmith et al. (2014) have used n-gram language models, Armstrong in his study (Armstrong, 2018) used topic models, and Orabi et al. (Orabi et al., 2018) used deep learning models such as 1-dimensional convolutional neural networks (CNN) and bidirectional long short-term memory (BiLSTM). Tsugawa et al. (Tsugawa et al., 2015) showed that the useful features for the prediction model are frequencies of word usage, together with topic modeling. They used the radial kernel SVM classifier for the dataset of 81 participants out of the 209 collected samples from questionnaires. The reported accuracy of the classifier was equal to 69%.

However some methods, based on lexicon, that were used in the early attempts to detect depression from social media posts have become outdated since nowadays many Twitter users very often use emojis (Chen et al., 2018). N-grams used for instance by (Coppersmith et al., 2014) are not useful in classifying tweets since there may appear a problem with classifier training when considering words that are not used in tweets (Barbosa, & Feng, 2010). Instead of n-grams the use of microblogging features (hashtags, emoticons, re-tweets, comments) to train an SVM classifier was suggested in (Pak, & Paroubek, 2010). They showed that the use of microblogging features resulted in higher accuracy.

Various supervised classifiers were used in studies concerning depression detection from social media posts, including support vector machine (SVM) (Aldarwish, & Ahmad, 2017; Sadeque, Xu, & Bethard, 2018), naïve Bayes (Pratama, & Sarno, 2015; Arora, & Arora, 2019), Support Vector Regression (SVR) (Arora, & Arora, 2019). Very good results with accuracy and F1-score over 90% were achieved in depression detection using Neural Networks (Lin, Hu, Su, Li, Mei, Zhou, & Leung, 2020; Tadesse et al., 2020; Zogan et al., 2022).

Li et al. (2020) proposed the CorExQ9 algorithm to analyze the COVID-19 related stress symptoms based on Twitter users posts at a spatiotemporal scale. The CorEx algorithm combined with clinical stress measure index (PHQ-9) allowed for reducing human interventions and human language ambiguity in social media data mining. They showed a strong correlation between stress symptoms and the number of increased new COVID-19 cases for some major U.S. cities.

Summing up the overview of works related to depression detection in social media posts based on sentiment analysis it can be concluded that data analyzed include text, emoticons and emojis (Cheng & Tsai, 2019; Abid, Li & Alam, 2020). There are two main approaches: rule-based and machine learning based sentiment analysis (Babu & Kanaga, 2022). According to (Salas-Zarate et al., 2022) the most commonly used lexicon-based feature extraction techniques are n-grams, bag of words, word embedding, tokenization, stemming and part-of-speech (POS) tagging. Classification techniques analyzed posts can be divided into 3 groups: binary (positive or negative), ternary (positive, neutral or negative) and multiclass distinguishing between different emotions (Jabreel & Moreno, 2019; Tao et al., 2019) or depression levels (Al Asad et al., 2019). Classification methods used in various research projects include Machine Learning techniques like SVM, Naïve Bayes, Multinomial Naïve Bayes, Random Forest, Ensemble vote classifier, or KNN (Ruz, Henriquez & Mascareno, 2020; Kumar, Sharma & Arora, 2019; Gaikwad & Joshi, 2016), as well as Deep Learning techniques like LSTM, BiLSTM, CNN and GRU (Chen et al., 2018; Cheng & Tsai, 2019; Bouazizi & Ohtsuki, 2016). Considering reported accuracy results the most effective are approaches using deep learning techniques and multiclass classification (Babu & Kanaga, 2022).

METHODS

It has been shown that sentiment analysis is an effective tool in emotion detection based on analysis if social media posts. Most of the research related to depression detection in social media is performed on labeled datasets. The goal of this research is to verify if there exists correlation between the results of sentiment analysis and the statistics related to depression. Positive correlation can indicate the usefulness of automatic posts' emotion polarity analysis for supporting depression detection and diagnosis. Therefore the research question was stated:
RQ: Is there a correlation between the number of negatively marked tweets extracted by sentiment analysis and statistics related to depression, mental illness and suicidal tendencies for the given region?
In the implementation of the system for tweets analysis MongoDB and Python programming language were used. In order to enable Python and MongoDB interaction PyMongo module was used. The process of the implementation was divided into the following steps: keyword selection, data acquisition, data rectification and analysis, and data visualization.

Keywords selection

Crucial step in obtaining proper data for analysis was selection of keywords related to depression and similar emotional states. Keywords selected were English words due to the popularity of this language in the world. However it limited the research results mostly to English-speaking countries. The keywords were detected based on the words used previously in related research (Chen et al., 2018; Movery et al., 2017; Nguyen et al., 2014; Jung et al., 2017) and based on their emotional score defined in the NRC Word-Emotion Association Lexicon (EmoLex) (Mohammad, & Turney, 2013). The choice of keywords was also influenced by the expressions used in PHQ-9 questionnaire ("suicidal", "feeling down", "feeling bad about yourself") and their synonyms.
Data was collected in three sessions. In the first session used keywords were: *depression, anxiety, suicide, suicidal*. Second session of data gathering included words such as: *broken, sad, afraid, alone*. Third phase combined words from sessions 1 and 2 with addition of word *depressed*. For the analysis all tweets containing at least one of the keywords were taken.

Data acquisition

Three 24-hour readings were performed at 2-day intervals. The total number of tweets collected was 3,015,617. Each measurement was analyzed separately, some of the data was also summarized collectively. For the purpose of data acquisition application *apps.twitter.com* was used, that allows the user to generate a token and a private key that enable to read tweets using API. A script was written in Python for reading tweets containing predefined keywords and saving them in json format. Collected data was stored as collections in MongoDB database.

Data rectification and analysis

For further analysis the rectification of collected data was performed. Stored tweets were grouped based on the keywords and then the sentiment analysis was performed. Sentiment analysis, or opinion mining, is a field of study that analyzes people's opinions, attitudes and emotions towards given entities. It uses a natural language processing (NLP) technique, that can determine if the examined text is positive, negative or neutral (Liu, 2015). For this purpose Python script using TextBlob library was written. TextBlob library enables to perform sentiment analysis based lexicon-based approach, using Natural Language ToolKit (NLTK) that gives an access to a large number of lexical resources. As a result the polarity and subjectivity of the analyzed text are returned. The range of polarity is [-1;1], where -1 indicates negative and 1 positive sentiment. Subjectivity is given in range [0;1] and the higher the score, the more personal is the analyzed opinion (Shah, 2020). For the analysis the tweets of sensitivity above 0.5 were selected and next their polarity was analyzed.

While analyzing tweets, there was a risk that a significant part of the results could be distorted by entries of organizations dealing with the prevention of depression, containing keywords such as *depression* or *suicidal*. Such entries should not be considered in terms of analysis in this project. Also, entries from people who have dealt with the problem and talk about their struggles with the disease may affect the correctness of the results. To partially reject this false data, it was decided to conduct a sentiment analysis. Thanks to such analysis, it was possible to determine which tweets are positive, negative and neutral. By rejecting positive and neutral tweets, it is possible to get rid of some of the data not related to the project's goal. This method allows for better data selection, but does not guarantee avoiding mistakes related to entries containing irony or hyperbolization, e.g. "Tomorrow is Biology test, I will probably kill myself". In order to achieve greater accuracy of the data, it would be necessary to carry out a more detailed analysis of entries and classification based on machine learning, using more features to classify entries.

Based on the emotional markers collected tweets were grouped into positive (polarity > 0), neutral (polarity = 0) and negative (polarity <0). At this stage the content of the database was limited to the following elements: user name, tweet text, time of entry, location and polarity. Tweets with no location defined were rejected from further analysis. Finally, data selection was performed in order to gather the following information: 1) distribution of the locations with largest number of tweets, 2) distribution of the locations with largest number of tweets with negative polarity, 3)most active users, 4) most active using posting tweets with negative polarity. Location of selected tweets was converted to geographical coordinates so in the process of visualization it was possible to display the most often appearing locations on the world map.

Data visualization

In order to make the obtained data more readable and understandable for readers, it was presented using different visualization methods. Data on the percentage shares of individual phrases and the percentage of negative, positive or neutral tweets, were presented using pie charts generated in Anaconda programming environment.

Another method of graphical representation of data are maps showing the intensity of the number of posts in a given region of the world. Such a map allows to intuitively understand which cities in the world have tweeted the most actively in terms of topics related to the searched keywords. To display the data on a map, the Folium library for the Python programming language was used. Aggregated data was used, using the latitude and longitude of each of the 20 cities as locations, city name as name, and number of tweets as frequency. The bubble radius for a given location is proportional to the number of tweets added from that location.

The next visualization method used was tornado charts for presenting comparison of tweets distribution in US states and statistics related to major depression episodes and suicidal deaths in the United States of America.

The fourth method of data visualization used were bar charts showing the number of tweets added in hourly time intervals. For each dataset, two such charts have been created for the two most popular locations, UK and US, and refer to the local time of this locations.

The last used method for data presentation was generating word clouds in order to show the frequency of use of the given keyword.

RESULTS

In the three 24-hour sessions 3,015,616 tweets were analyzed, 520,829 of which were assigned with the known location. Graphical distribution of the emotional markers percentage for each session is shown in Figure 8. Table 1 shows the number of tweets collected in each session.

Table 1. Characteristics of tweets collected in 3 sessions

	All tweets	Negative	Neutral	Positive	Tweets with known location
Session 1	373167	120146	127478	125543	67773
Session 2	1071171	549918	227142	294111	183669
Session 3	1571278	765995	371998	433285	269387

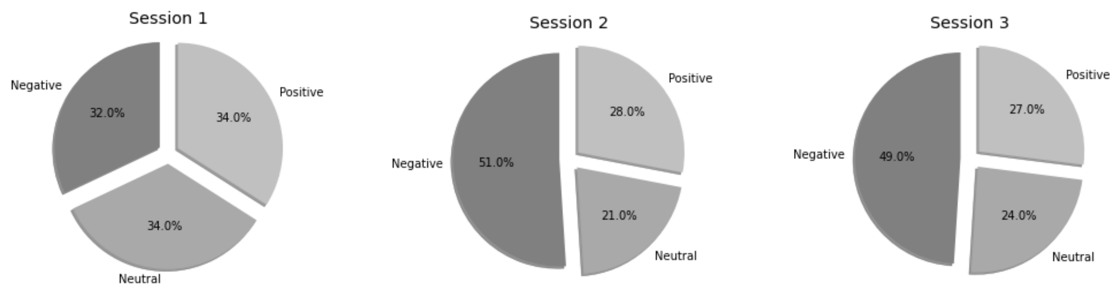

Figure 8. Distribution of the emotional markers percentage for each session

Session 1

In session 1 373,167 tweets were analyzed. Of the tweets with the keyword *depression*, only 29% (18,747 out of 64,490 entries) had a negative character. In the case of tweets containing the word *anxiety*, the disproportion was even greater. As many as 58% of entries were classified as positive, 24% as neutral and only 18% as negative.

Reading the entries containing this keyword, it could be observed that it is often used by health organizations, units dealing with the prevention of depression and by public profiles of medical facilities and research centers. In the case of this keyword, focusing only on entries classified as negative can bring particularly great benefits when it comes to improving the quality of data. In the case of tweets containing the *suicide* keyword only 23% of tweets were identified as positive, 31% as negative and 46% as neutral. In the case of entries containing the word *suicidal*, there is a noticeable clear advantage of entries with negative markings - 91% of entries. The neutral and positive entries take on the values of 5% and 4% respectively.

Based on the above data, it is possible to observe the proportion of negative tweets to all tweets for given keywords. The highest negative character could be observed for the word *suicidal* (91%), successively for the word *suicide* (31%), *depression* (29%), and the weakest negative character was noticeable for the word *anxiety* (18%). Because the percentage share of tweets containing the given word was not equal, it was decided to check the percentage share of keywords after rejecting positive and neutral tweets. The largest share of all tweets classified as negative had entries containing the keyword *suicidal* (40%). Subsequent entries include the words: *depression* (21%), *anxiety* (20%) and *suicide* (19%) (Figure 9).

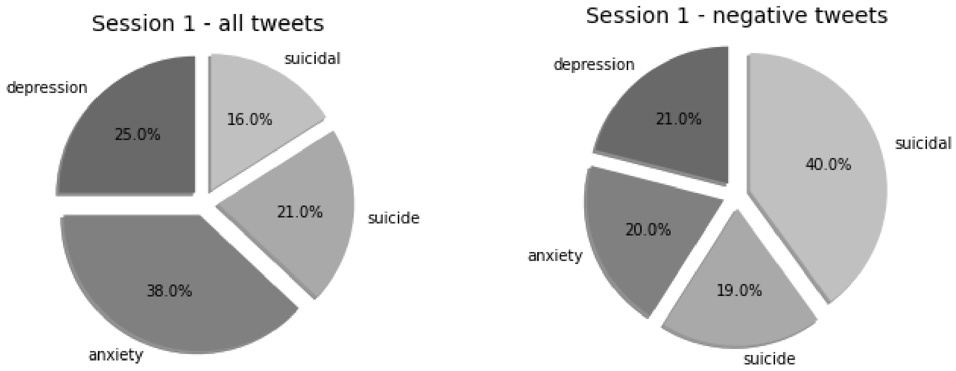

Figure 9. Share of keywords in all analyzed tweets and in tweets with negative emotional character for session 1

Based on the tweeds that had correct location data, the places in the world with most active users were found. The process of checking city activity for the set of tweets identified as negative by the sentiment analysis was performed. In this case London was the most active city. Then, the next eight most active cities are in the United States. On the map with negative tweets (Figure 10) greater activity on the north-eastern side of the United States can be noticed, and smaller in the south-west of the map. Also visible are single active locations in Africa - Lagos in Nigeria, India - Mumbai and two cities in Australia - Sydney and Melbourne.

Figure 10. Intensity map of tweets with negative character containing keywords for session 1

Session 2

The total number of tweets collected during the second session was equal to 1,071,171. The most frequent tweets contained the word sad (90,052, 47% of all entries) and alone (304,149, 29% of all entries). The words broken and afraid had respectively 14% and 10% shares. After the sentiment analysis, 294,111 positive entries were received (51%), 227,142 neutral (28%) 549,918 negative (21%). It means that this set of data in case the used terms is much more "negative" than keywords used in the first session. This may be due to the fact that in the previous set of data the words used were more formal, thus more often used by institutions than by private individuals.

Based on the above data, it is possible to observe the proportion of negative tweets to all tweets for given keywords. The largest share of all tweets classified as negative had entries containing the keyword sad (61%), next was the keyword broken (17%), afraid (12%) and alone (10%) (Figure 11).

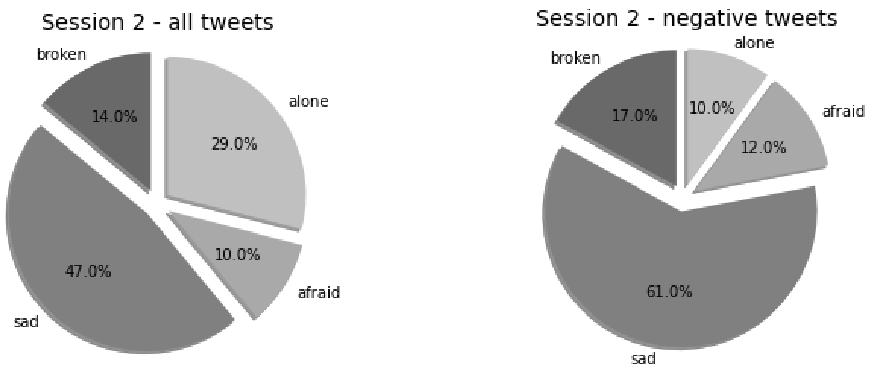

Figure 11. Share of keywords in all analyzed tweets and in tweets with negative emotional character for session 2

On the basis of this data, a map was created, which using bubbles shows the activity of users from a given location. The map shows that the most tweets were read from the Great Britain and the United States. In the United States, the highest concentration of bubbles is also visible, i.e. many locations close to each other have been classified as the most active. There is also a lot of activity in Nigeria, South Africa and Pakistan. It can be assumed that such disproportion in tweets flowing from English-speaking countries to other locations results from the fact that the search keywords were in English (Figure 12).

Figure 12. Intensity map of tweets with negative character containing keywords for session 2

Session 3

During session 3 1,571,278 tweets containing predefined keywords were collected. The most commonly used keywords in session 3 were: *anxiety* (34%), *alone* (19%) and *suicide* (13%). The words *broken* and *afraid* were present in 8% of cases, while *depressed* and *depression* in 6% of cases. The word *suicidal* is a negligible part of all entries. Of all the data collected, after sentiment analysis, 49% were classified as negative tweets, 27% were positive and 24% were neutral. After rejecting positive and neutral tweets, the largest share of all tweets classified as negative had entries containing the keyword *sad* (46%). Next were entries containing the word *suicide* (17%), *broken* (11%), *afraid* (10%) and *alone* (9%). The words *anxiety*, *depression* and *suicidal* were negligible (Figure 13).

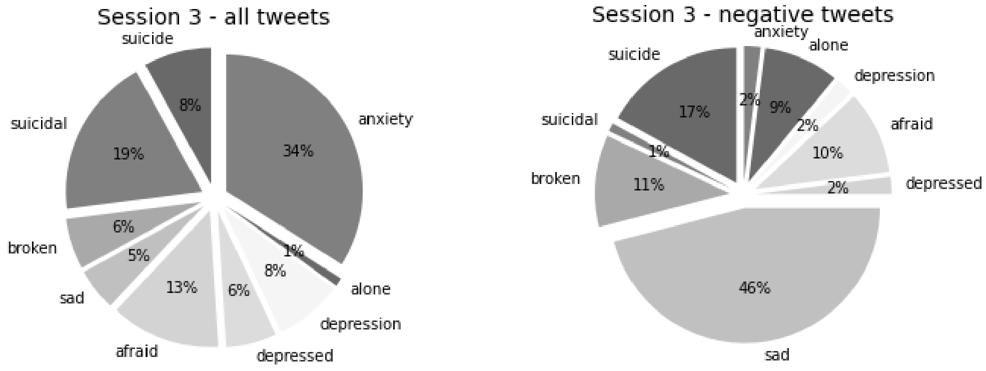

Figure 13. Share of keywords in all analyzed tweets and in tweets with negative emotional character for session 3

Then, based on tweets that had valid location data, an analysis was made of which places in the world were most active during measurements. The most active city turned out to be London, from which 10,678 entries were made, followed by Los Angeles with 8,467 tweets. The map shows that again most tweets were read from the Great Britain and the United States (Figure 14).

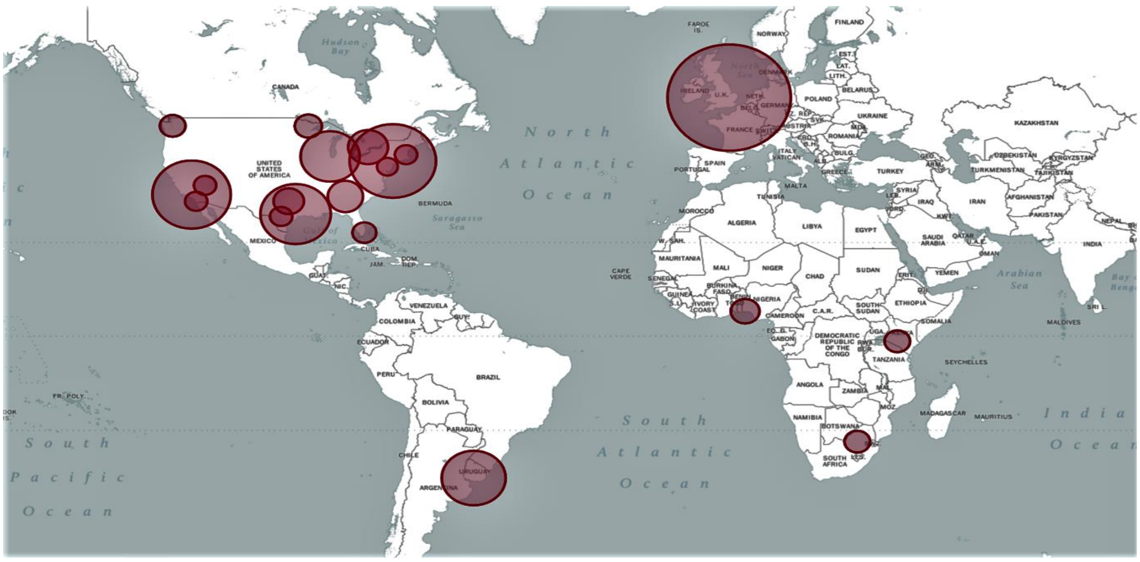

Figure 14. Intensity map of tweets with negative character containing keywords for session 3

Summary of the results

Total number of gathered tweets in the three session was equal to 3,015,617. For all collected data, after sentiment analysis, 48% of tweets were found to be negative, 28% positive and 24% neutral. The largest negative character could be observed for the word *sad* (79.5% of this word usage), 77.5% for *broken*, 76% for *suicidal* and 76% for *afraid*. A much weaker negative character could be observed in the case of the word *alone* (30.5% of all occurrences of this word), *depression* (27%) and *anxiety* (21.5%). The percentage share of each keyword in all the three sessions classified as negative (Figure 15), neutral (Figure 16) and positive (Figure 17) are presented in the form of pie charts and word clouds.

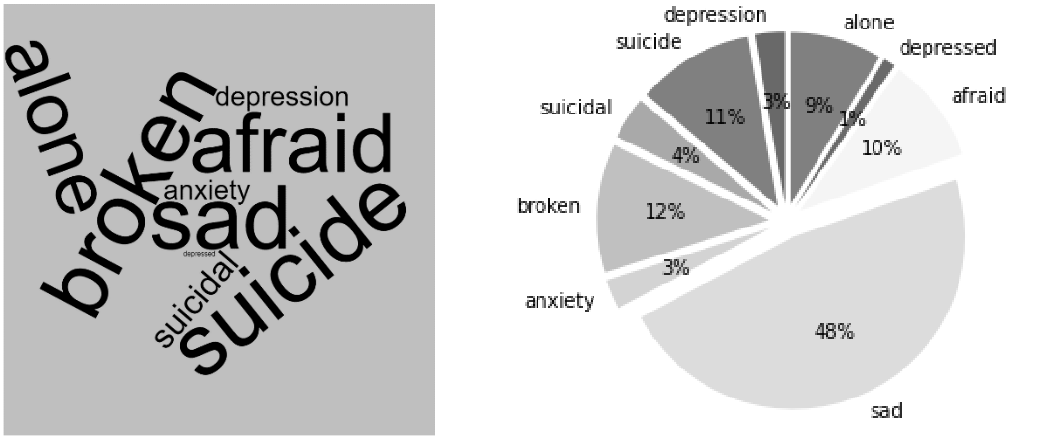

Figure 15. Share of keywords in tweets with negative character

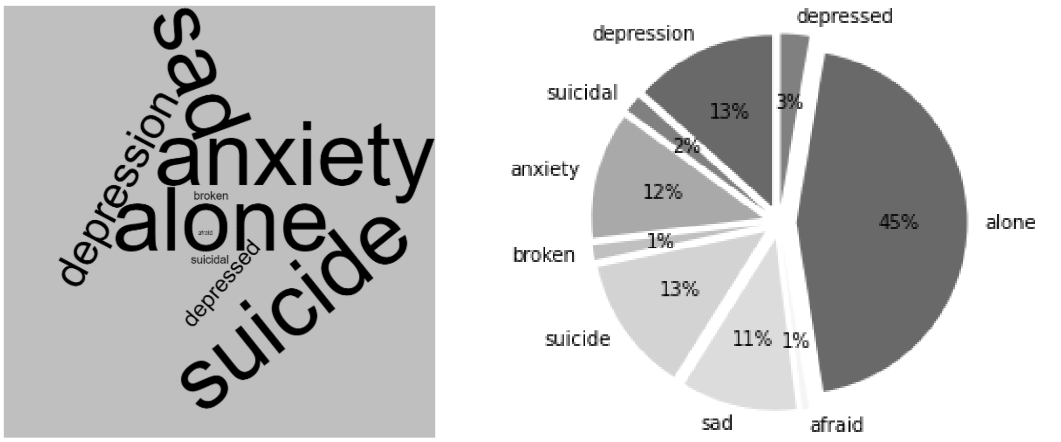

Figure 16. Share of keywords in tweets with neutral character

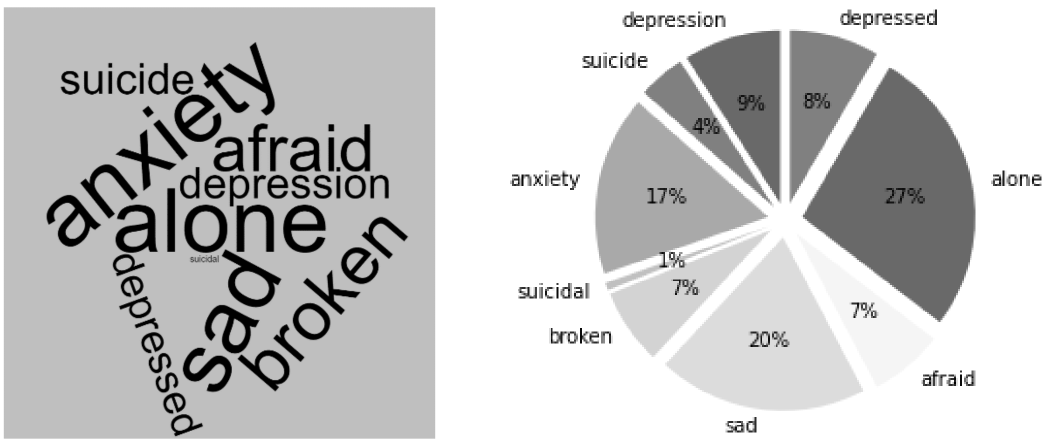

Figure 17. Share of keywords in tweets with positive character

It has been observed that often tweets containing the terms depression or anxiety are positive entries from organizations and pro-health institutions. With the help of sentiment analysis, it was possible to partially reduce this type of data by deleting data classified as positive and neutral. After this procedure, the number of entries made available by the most active users decreased by 55%. For some of the entries (around 18%), the location was read. For these tweets, the analysis of the most active locations was carried out. Users from London in the UK turned out to be the most active ones, followed by users from different cities in the United States. Also, a large number of tweets came from places like Nigeria, Kenya, South Africa and Pakistan.

For the final stage of the results analysis only the negatively marked tweets from the USA were selected in order to verify the validity of the research question stated. The percentage of all tweets and negative tweets in the ten states of the USA with highest Tweeter activity for all 3 sessions is presented in Figure 18.

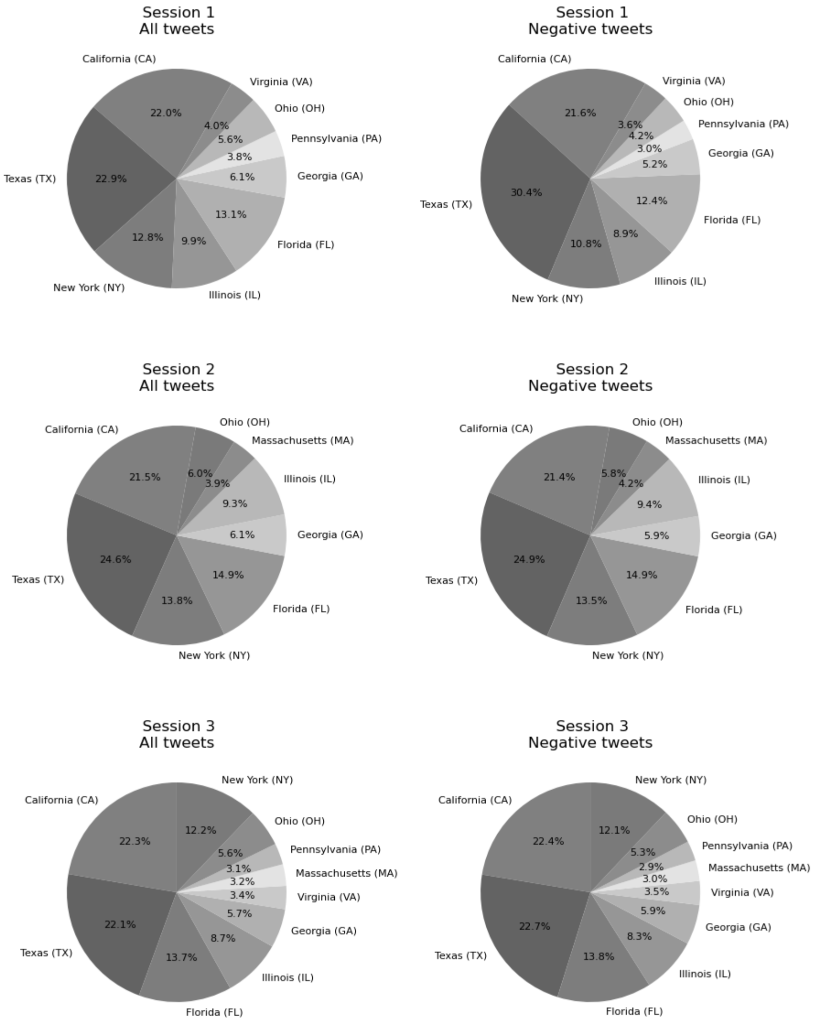

Figure 18. Percentage share of tweets with known location extracted in the 3 sessions for the 10 US states with largest Tweeter activity

DISCUSSION

The distribution of Twitter/X activity related to depression in the United States of America (Figure 19) was compared with available official screening statistical data concerning: Major Depressive Episodes (MDE) among young people who reported no medical help, any mental illness (AMI) among people who reported no medical help (Nguyen, Hellebuyck, & Halpern, 2017), and with numbers of suicidal deaths in 2017 (Alltucker & Price, 2018). In all cases 8 out of first 10 US states overlap with the list of 10 tweeting states from the research (Table2).

Table 2. Comparison of the nnumber of negative tweets with suicidal deths statistics (Alltucker & Price, 2018) and screening results for persons with MDE and AMI who reported receiving no medical help (Nguyen, Hellebuyck, & Halpern, 2017)

Presented research		MDE with no medical help		AMI with no medical help		Suicidal deaths	
US State Code	No. of tweets	US State Code	MDE	US State Code	No. of people (x1000)	US State Code	Suicidal Deaths
CA	14457	**CA**	**47000**	**CA**	**5919**	**CA**	**4294**
TX	13124	**TX**	**32000**	**TX**	**3657**	**TX**	**3488**
FL	8426	**NY**	**28000**	**NY**	**321**	**FL**	**3143**
NY	7451	**OH**	**21000**	**FL**	**3094**	**PA**	**1970**
IL	5218	**IL**	**20000**	**PA**	**2165**	**OH**	**1707**
GA	3480	**FL**	**19000**	**OH**	**2140**	**NY**	**1679**
OH	3229	MI	19000	**IL**	**1930**	**IL**	**1415**
MA	1904	**PA**	**16000**	NC	1783	**GA**	**1409**
VA	1342	NC	14000	MI	1652	NC	1373
PA	1113	**MA**	**11000**	**GA**	**1635**	MI	1364

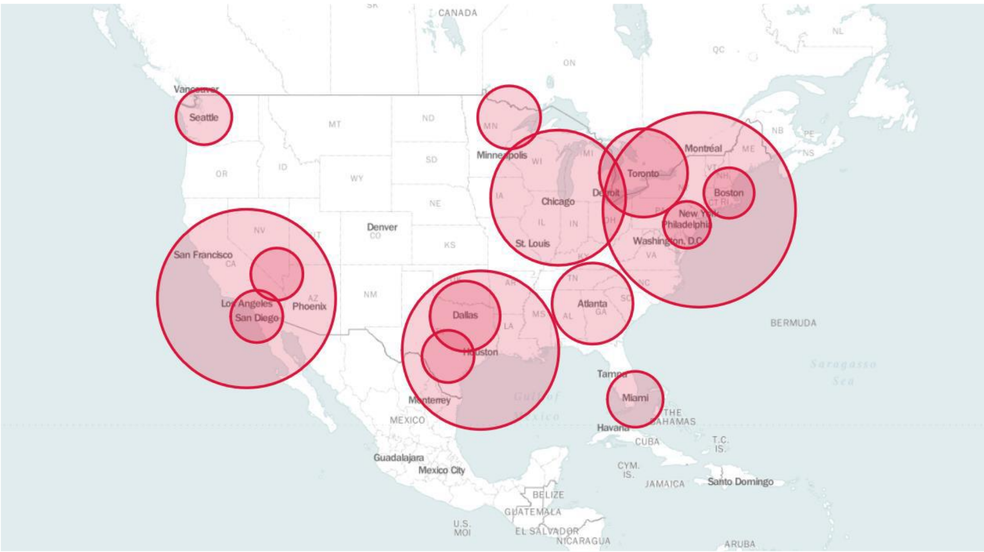

Figure 19. USA intensity map of tweets with negative character containing keywords defined for all sessions

It was observed that tweets identified as related to depression corresponds well with US suicidal deaths statistics, as well as with reports considering persons with depression who did not receive professional medical help or received it only partly. Moreover, the numbers related to persons suffering from mental illness who did not receive professional help also correspond well with the presented tweets distribution.

The numbers of negatively marked tweets were also compared with the results of screening reports related to depression and self-harm and suicidal thoughts (Nguyenet al., 2017). The correlation coefficient was calculated for the sets containing number of screeners diagnosed with moderate, moderate-severe and severe depression (Figure 20), as well as with screeners reporting having suicidal thoughts more than half of the days and almost every day (Figure 21). The results are presented in Table 3. It can be observed that the sets are highly correlated.

Table 3. Correlation coefficients for negative tweetss numbers and screening results in US states

	Moderate depression	Moderate-severe depression	Severe depression	Suicidal thoughts over half of the days	Suicidal thoughts almost every day
Correlation coefficient	0,90	0,93	0,95	0,92	0,94

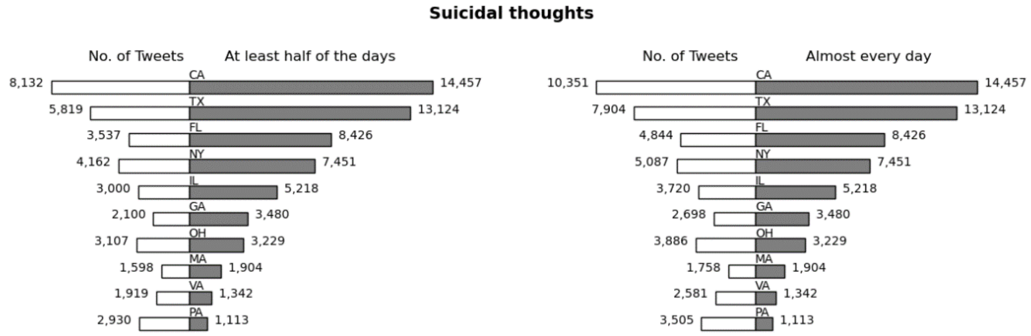

Figure 20. Comparison of the number of negative tweets in top 10 US states and number of persons reporting suicidal thoughts in screening tests

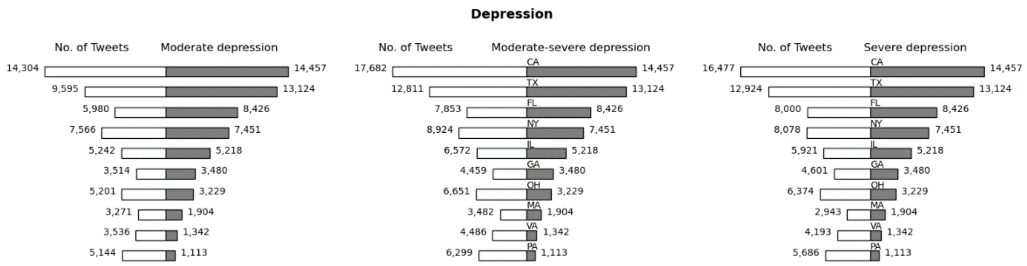

Figure 21. Comparison of the number of negative tweets in top 10 US states and number of persons reporting depression

It could be then construed that people with undiagnosed depression and suicidal thoughts are more often expressing their feelings in social media, looking in this way for help with their emotional problems. This thesis is confirmed by the statistics presented in (The Clinical Committee, 2019) showing that people with depression use social media more often (Pantic, 2014) and 55% of persons with high depression symptoms engage in over 30 social media sessions per week. Also people with suicidal tendencies post often on social media, informing about their feelings, expressing suicidal thoughts (Sueki, 2013; Gunn & Lester, 2015). The review presented in (Zubair, Khan & Albashari, 2023) suggests that using social networks is correlated with psychological problems such as anxiety, depression, insomnia and sense of mental deprivation. This statement is in accordance with the presented results of the study, confirming that people with depression, mental disorders and suicidal tendencies post about their mood, feelings and thoughts, what can be detected using sentiment analysis.

An additional analysis was performed to look into daily activity of users tweeting about sadness and depression. There was a decrease in activity during the night hours between 1 and 6 in the morning – corresponding to generally lower Twitter activity in the night, stable high level of activity during the day, with a maximum in hours 20-21 (Figure 21).

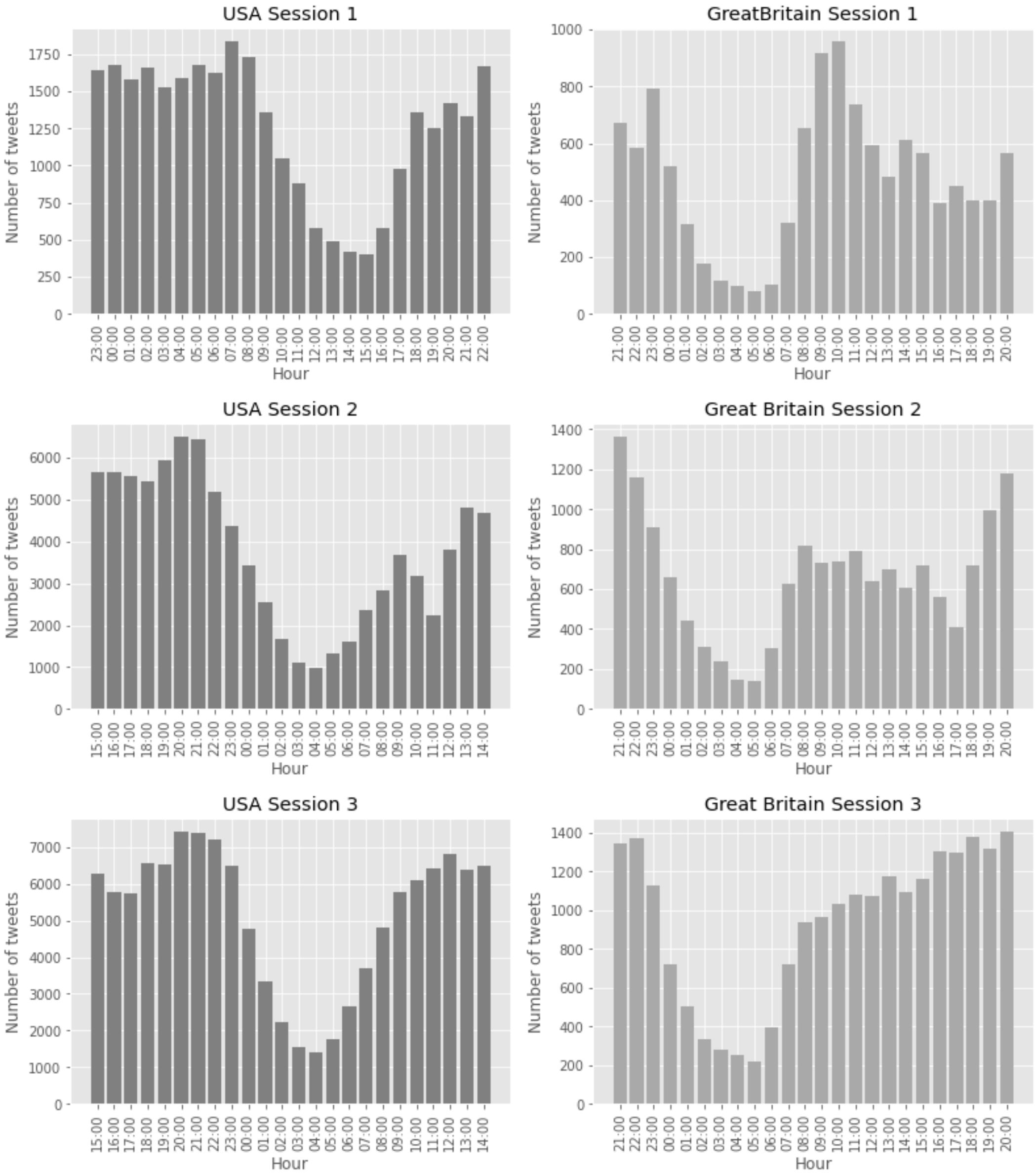

Figure 22. Daily activity of Twitter users in USA and UK during 3 sessions

CONCLUSIONS

Depression is an increasing health problem in the world. It can be called a plague despite the availability of effective treatments for this disease. About 50% of people who suffer from depression are undiagnosed. At present, it is important to find as many depression patterns as possible to improve the identification process. The aim of the work was to assess if analysis of tweets can serve as a proxy for assessing depression level in the society. Performed research allowed to identify certain patterns of Twitter users' activity, adding posts about depression, suicides, sadness or loneliness, to broaden the general knowledge of depression and provide additional data that could help to prevent this disease. The work focused primarily on Twitter activity in Great Britain and the United States. This is due to the use of keywords in English. To extend the work, it would be necessary to use translations of given words for a larger group of languages.

It should also be taken into account that in some African countries social networks are not used due to the lack of access to computers and smartphones, and in Asian countries such as Korea, China, social networks other than Twitter are more popular. For tweets from the United States, the activity maps were compared with a map of the percentage of people with diagnosed depression and a correlation was observed. Collected data allow to observe certain tendencies related to the activity in social media of people who provide entries on subjects related to depression, sadness, fears, or loneliness. Of these people, potentially, some may suffer from undiagnosed depression. Understanding the patterns of their behavior on the Internet may contribute to improving the ability to recognize and diagnose this disease, and it may also enable the introduction of systems for detecting persons who are at risk. This method could be improved and expanded so that the amount of data obtained is greater and the results more reliable.

To improve the accuracy of the results it would be necessary to conduct a more targeted research on tweets from people diagnosed with depression but not treated, healthy people and people diagnosed with depression during the treatment process. Tweets from an extended time span from selected individuals should also be analyzed in order to uncover differences between the activity of sick, healthy and treated people.

IMPLICATIONS FOR THEORY AND APPLICATIONS

The results indicate that analysis of posts in social networks, if carefully performed, can serve as an indication of society level of depression. It is probable that this approach could be extended to other diseases, especially of psychological nature. In the past Twitter data has been shown to be a useful predictor of e.g. stock exchange prices (Bollen, & Mao, 2011). It indicates that it reflects population mood and emotions well, to an extent to it impacts decision making.

Considering these results, public institutions should invest in project that would deepen this understanding and extend to other social networks, which might be more appropriate for other populations and social challenges.

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FACTORS INFLUENCING DIGITAL ENTREPRENEURSHIP INTENTION AMONG UNDERGRADUATE BUSINESS STUDENTS IN JORDAN

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Abstract: *The digital revolution has completely changed the business structure, offering entrepreneurs and economies tremendous opportunities. The Jordanian government and universities recognized this potential and took steps to foster a digital entrepreneurship culture. However, despite these efforts, universities in Jordan have been relatively slow in supporting and integrating digital entrepreneurship culture. This study investigated the factors influencing digital entrepreneurship intention among 399 undergraduate students in Jordan. Partial Least Squares Modeling was used to analyze the data. The empirical findings indicated that digital entrepreneurship intention is directly influenced by attitude towards entrepreneurship and perceived behavioral control and indirectly by personality traits. However, subjective norms, digital literacy, and perceived university support did not significantly impact it. The findings of this study contribute to the growing body of knowledge on the role of digital literacy and socio-psychological factors in driving digital entrepreneurial intentions, offering valuable insight for future policy initiatives and educational strategies.*

Keywords: *Digital entrepreneurship intention, personality traits, digital literacy, perceived university support, entrepreneurship in Jordan.*

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INTRODUCTION

In the contemporary landscape of global economies, nations grappling with high unemployment rates encounter multifaceted challenges that extend beyond economic concerns. The issue of unemployment, especially among the youth population, is not only a matter of economic stagnation but also a social and political predicament (Ahmed et al., 2017). In this context, entrepreneurship alleviates unemployment woes and contributes to holistic economic and societal development (Mahadea et al., 2011). Digital technologies have revolutionized the entrepreneurial sphere in recent decades, redefining traditional practices and opening new opportunities (Hull et al., 2007; Rippa & Secundo, 2019). In the digital realm, entrepreneurs now access an interconnected ecosystem, empowering them to connect, network, and operate their businesses more efficiently and effectively (Kovács et al., 2022; Turban et al., 2006). This digital transformation has democratized access and significantly lowered entry barriers, allowing aspiring entrepreneurs to launch and grow their ventures with limited resources (Youssef et al., 2020). As a response, the Government of Jordan has established a Ministry for Digital Economy and Entrepreneurship to facilitate the digital transformation process (*Minister of Digital Economy and Entrepreneurship*, 2019). However, this initiative requires collective efforts of all stakeholders. Universities play a vital role in equipping students with the skills and mindset required to seize digital entrepreneurship opportunities and overcome unemployment challenges (Saeed et al., 2015).

Researchers have employed the theory of planned behaviour (TPB) to identify the driving force of entrepreneurial intentions and actions (Liñán & Chen, 2009). This theory revolves around three essential elements, namely attitudes towards entrepreneurship, subjective norms and perceived behavioral control (Ajzen, 1991). Internal (like personality traits) or external factors (like perceived university support) have been studied separately but not in a combined way (Karimi et al., 2017). Despite digital literacy presents a vast opportunity for success in digital startups (Mudasih et al., 2021), only a few articles have studied the impact of digital literacy on digital entrepreneurship (Suparno et al., 2020). This research aimed to fill the previous gaps by examining the effect of internal and external factors and digital literacy on young individuals' digital entrepreneurial intention (DEI). The article followed this structure: literature review, methodology, results, discussion, conclusion, and implications.

LITERATURE REVIEW

Digital Entrepreneurship in Universities

Information and communication technologies (ICTs) have changed business practices recently (Farani et al., 2017). The wide spread of digital technologies removes entry barriers and unnecessary sunk costs, reduces the risk of creating a new business, and provides new opportunities to entrepreneurs (Hull et al., 2007; Youssef et al., 2020). Digitalization creates new market needs for new types of businesses and entrepreneurs, making it more feasible for many people to engage in entrepreneurial activities.

Digital entrepreneurship has a profound impact on universities and students alike. For universities, it necessitates rethinking educational approaches to ensure that students are equipped with the skills and knowledge required to thrive in the dynamic digital landscape (Sousa et al., 2019). That often involves integrating entrepreneurship and digital literacy into the curriculum, fostering innovation hubs, and establishing strong industry partnerships. Universities become hubs for fostering innovation and incubating digital startups (Liñán & Chen, 2009). Digital entrepreneurship offers students a unique avenue to apply their classroom knowledge to real-world scenarios. It empowers them to become proactive creators rather than passive consumers of technology (Turban et al., 2006). Through digital entrepreneurship, students gain practical experience, develop problem-solving skills, and have opportunities to launch their businesses while still in school, enhancing their career prospects and contributing to economic growth and innovation (Suparno et al., 2020). Digital technologies also allow students to start their businesses while still in school, opening the possibilities to turn the education period into a successful business venture (Rippa & Secundo, 2019; Youssef et al., 2020).

The Theory of Planned Behavior

The Theory of Planned Behavior (TPB) is widely accepted in social psychology, explaining the relationship between attitudes, intentions, and behavior (Ajzen, 1991). TPB has been notably used in entrepreneurship to comprehend the driving forces behind entrepreneurial actions (Krueger & Carsrud, 1993). TPB posits that an individual's intentions are influenced by three critical components: attitude, subjective norms, and perceived behavioral control (Ajzen, 1991). Specifically, in this study, DEI refers to a person's desire and motivation to begin an online business utilizing digital technology, social media, and e-commerce to gain visibility and access a larger customer base (Al-Mamary & Alraja, 2022).

Attitude Towards Entrepreneurship

Attitude Towards Entrepreneurship (ATE) is defined as a person's positive/negative evaluation of a behavior (Liñán & Chen, 2009). Entrepreneurship studies have consistently proved the pivotal role of attitudes in shaping entrepreneurial intentions (Fatoki, 2020). A positive attitude toward entrepreneurship is associated with a higher chance of starting one's business (Anwar et al., 2021). Moreover, a favorable attitude towards entrepreneurship positively influences the perception of entrepreneurship as an appealing career choice, reinforcing the notion that attitudes play a crucial role in guiding individuals' aspirations (Alkhalaileh, 2021). Studies showed that women's digital intentions in Saudi Arabia are majorly influenced by their attitudes (Aleidi & Chandran, 2019; Alzamel et al., 2019).

Subjective Norms

Subjective norms (SN) represent the perceived social pressure to perform any behavior (Liñán & Chen, 2009). Individuals are more inclined to engage in a particular behavior if they perceive that it is socially approved by their immediate social circle (Ajzen, 1991). This concept aligns well with the notion that societal norms can significantly sway individual intentions in entrepreneurship (Begley & Tan, 2001; Mueller & Thomas, 2001). Empirical research by Begley and Tan (2001) found that perceived support from family and friends positively influenced individual intentions toward entrepreneurship. Similarly, Biswas & Verma, (2021) identified a positive relationship between social support and entrepreneurial intentions. These findings collectively suggest that individuals are more likely to pursue entrepreneurial paths when they perceive social and environmental support.

Perceived Behavioral Control

Perceived Behavioral Control (PBC) reflects the level of confidence an individual has in their capability to overcome obstacles and successfully engage in the intended behavior. This concept is crucial in understanding DEI as the perceived ease/difficulty of starting a digital business can strongly influence motivation (Hassan, 2020; Karimi et al., 2017). Ajzen (1991) states that higher perceived control over a behavior leads to stronger intentions. That aligns with the entrepreneurial context, where individuals with greater perceived control over the challenges are likelier to start a business (Alzamel et al., 2019). Studies have consistently demonstrated that PBC significantly predicts entrepreneurial intentions. Hassan (2020) and Karimi et al. (2017) found that individuals who perceived themselves as possessing the necessary skills, resources, and opportunities were more likely to express intentions to engage in digital entrepreneurial activities. TPB provides a framework for understanding and predicting entrepreneurial intentions through ATE, SN, and PBC. Therefore, the following hypotheses were formed:
H1: ATE (a), SN (b), and PBC (c) influence the DEI of undergraduate students in Jordan.

Digital Literacy

Digital Literacy (DL) and entrepreneurial intent have been widely studied in the Information and Communication Technology field (Mudasih et al., 2021). Digital literacy involves obtaining, analyzing, and conveying information using digital tools and networks (Warschauer et al., 2010), which is essential for the success of digital entrepreneurs (Suparno et al., 2020). These skills are important in different relations in e-society, including those typical for business communications with authorities (Bilan et al., 2023) and use of financial services for business (Pakhnenko et al., 2021; Straková et al., 2022). The relationship between digital literacy and entrepreneurial intention has been the subject of numerous research. In their article, Bayrakdaroglu and Bayrakdaroglu (2017) found that digital literacy substantially influences internet entrepreneurship intentions more than financial literacy. This assertion resonates with the findings of Suparno et al., (2020), who illuminated a positive correlation between students' aspirations for digital business ventures and their creativity and digital literacy levels. In alignment with that, the following studies also found a positive correlation between entrepreneurship intention and digital literacy across diverse contexts (EL-SISI, 2022; Hardika et al., 2022). Therefore, the following hypothesis was investigated:
H2: Digital Literacy influences the digital entrepreneurial intentions (DEI) of undergraduate students in Jordan.

Perceived University Support

Universities have become increasingly vital in creating a supportive ecosystem to nurture entrepreneurial culture in societies (Guerrero et al., 2016; Volchik et al., 2018). Several studies have linked various facets of perceived university support (PUS) to entrepreneurial activity, making PUS an essential factor in entrepreneurial intention (Kraaijenbrink et al., 2010). While educational support is undoubtedly pivotal, a more comprehensive approach is required. Cultivating a conducive environment for entrepreneurship, encompassing conceptualization and business development support, becomes imperative in changing students' intent to start their businesses (Saeed et al., 2015).

According to Saeed et al. (2015), perceived educational support (PES) measures how much students perceive their academic institution offers tools, mentorship, and advice to nurture entrepreneurial knowledge and skills. That was exemplified by the work of Nguyen and Duong, (2021) highlighting the strong correlation between PES, subjective norms, entrepreneurial self-efficacy, and EI among Vietnamese students. In a similar vein, Shi et al., (2020) discovered that PES had a direct impact on independence- and growth-oriented intentions, underscoring the broader influence of perceived support on different facets of intention. In the context of digital entrepreneurship among undergraduate students in Jordan, perceived educational support gains heightened relevance. As students navigate the complexities of digital business ventures, the availability of resources, mentorship, and advice within the academic environment could significantly mold their intentions to engage in digital entrepreneurial activities.

Saeed et al. (2015) described that Perceived Concept Development (PCD) measures how much students believe their academic institution offers opportunities to develop and polish their entrepreneurial ideas. PCD has been recognized as a critical element in forming entrepreneurial intentions. For instance Mustafa et al., (2016) demonstrated that perceived concept development and proactive personality traits significantly influenced entrepreneurial inclination. That underscores the integral connection between the availability of opportunities for idea development and the formation of entrepreneurial intentions. Additionally, research by Lestari et al., (2022) found that perceived concept development support positively affects self-efficacy, which, in turn, influences students' intentions to embark on entrepreneurial endeavors. That links the availability of concept development support and the psychological factors that drive intentions.

As Kraaijenbrink et al. (2010) articulated, Business Development Support (BDS) relates to how students feel their university offers resources and advice for the practical aspects of beginning a business, such as funding and legal concerns. BDS has been recognized as a significant predictor of EI in numerous research. For instance, Su et al. (2021) demonstrated the substantial impact of BDS on the perception of behavioural control and attitudes toward entrepreneurship. That underscores the influential role of practical support in shaping perceptions and attitudes that ultimately influence entrepreneurial intentions. According to other studies (Lestari et al., 2022; Saeed et al., 2015), perceived concept development support positively impacts self-efficacy, indirectly influencing students' intention to start their own businesses.

In conclusion, universities can be essential in developing and supporting the next generation of entrepreneurs. By actively fostering an entrepreneurial mindset and creating a

supportive ecosystem, universities have the unique opportunity to cultivate the knowledge, skills, and attributes required for entrepreneurial success. Therefore, the following hypotheses were proposed:
H3: PES (a), PCD (b), BD (c) influence DEI of undergraduate students in Jordan.

Personality Traits

The interplay between personality traits and entrepreneurial intentions has garnered considerable attention in scholarly discourse, offering insights into the complex dynamics that influence individuals' inclination to engage in entrepreneurial activities (Tran & Korflesch, 2016). The history of research in this area may be traced to the ground-breaking work of David McClelland in the middle of the 20th century, highlighting the pivotal role of personality traits, particularly the need for achievement, in driving business success (McClelland, 1961). Subsequent research explored various traits' links to entrepreneurial intention, including risk-taking, locus of control, and innovativeness (Anwar et al., 2021; Roy et al., 2017). Risk-taking propensity (RT) is the willingness to take risks and tolerate ambiguity (Jackson, 1979). RT is one of the most widely studied personality traits influencing the decision to start a business (Vodă et al., 2019). High-risk takers are more inclined to engage in entrepreneurial activities, ready to take calculated risks and embrace uncertainty (Keat et al., 2011). This trait enables individuals to identify entrepreneurial opportunities that others might overlook and motivates them to take action upon those opportunities (Vodă et al., 2019).

According to Hermawan et al. (2016), the locus of control (LC) is the degree to which a person believes they have control over their own fate. People with an internal locus of control think that their choices and actions directly affect the results they get (Mueller & Thomas, 2001). As opposed to this, people with an external locus of control blame luck or fate for their triumphs and failures (Hermawan et al., 2016). Innovativeness (I) refers to an individual's ability to generate new ideas and think creatively (Robinson et al., 1991). Individuals with high levels of innovativeness are more likely to engage in entrepreneurial activities because they can better identify new and innovative business opportunities (Biswas & Verma, 2021). Innovativeness is also associated with a willingness to take risks and experiment with new ideas, which is essential for entrepreneurial success (Ahmed et al., 2019). The need for achievement (NA) is a critical personality attribute that affects entrepreneurial intention. According to McClelland (1961), NA is the desire to perform above average, complete challenging tasks, and outperform others in performance. Individuals with high levels of need for achievement are more likely to engage in entrepreneurial activities because they are driven to succeed and achieve their goals (Batool et al., 2015; Ž. Zovko, 2020). However, they may also be more risk-averse and less willing to take calculated risks. The need for achievement is crucial when examining entrepreneurial intentions, but it should be considered along with other factors to ensure success (McClelland, 1961).

Prior research has demonstrated that personality traits can impact entrepreneurial behavior and intentions, either directly or indirectly (Biswas & Verma, 2021; Munir et al., 2019). For instance, a study conducted on 261 business stream students in Saudi Arabia reported that risk-taking directly and positively affected entrepreneurial intention. Furthermore, a study of 663 students from Indian universities found that risk-taking, locus of control, and innovativeness positively impacted the attitude toward entrepreneurship, perceived behavioral control, and entrepreneurial intention directly (Anwar et al., 2021). Karimi et al. (2017) investigated the relationship between personality characteristics, contextual factors, and entrepreneurial intentions in Iran. The study found that the need for achievement, locus of control, and risk-taking are directly related to ATE and PBC. The study by Mahmood et al., (2019) reinforced these connections by showcasing the positive and significant impact of the need for achievement, locus of control, proactive personality, and innovativeness on attitude toward entrepreneurship among Asnaf millennials, a group of socially disadvantaged people in Malaysia. In summary, empirical research provides robust support to the interplay between personality traits and entrepreneurial intentions, as evidenced in diverse contexts, underscores the significance of these traits in shaping individuals' propensities to engage in entrepreneurial endeavors.

As a result, we proposed the following hypothesis: RT (H4), LC (H5), I (H6), NA (H7) have an influence on both ATE (a) and PBC (b). All hypotheses were summarized in Figure 1.

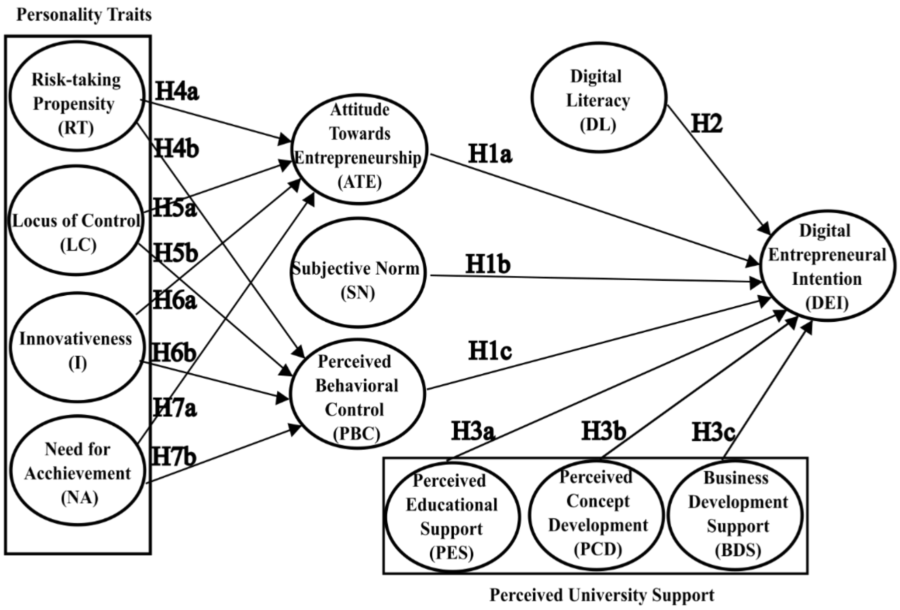

Figure 1. Conceptual Framework
[Source: Mohammad Younis Al Khalaileh PhD research, 2022]

METHODOLOGY

This study investigates the digital entrepreneurial intentions among Business students in Jordan as they often choose business-related careers due to their enrolment in various business programs (Millman et al., 2010; Yordanova et al., 2020). The study used a quantitative research approach and a survey to collect data. The population comprises 15,368 bachelor's business students who enrolled in a Business School degree at eight universities offering entrepreneurial education and incubation services (The Ministry of Higher Education and Scientific Research, 2022). The required sample size needed for this study was 375 units (Krejcie & Morgan, 1970) and the actual sample size was 399. A quota sampling technique was used to select the participants. The sample was stratified based on the university to ensure that the participants' distribution was proportional to the total population. The survey used in this study was designed based on a literature review of the internal and external factors that influence digital entrepreneurial intentions. DEI and ATE were developed on a 5-item scale, PBC on a 4-item scale, and SN on a 3-item scale by (Liñán & Chen, 2009). At the same time, DL was developed as a 9-item scale (Ng, 2012). Moreover, PUS was developed on a 13-item scale by Saeed et al. (2015). RT, LC and I were all developed on a 4-item scale and adopted by Anwar et al. (Anwar et al., 2021), Zellweger et al. (2011) and Jackson (1979). Finally, Zovko et al. (2020) used five items to measure NA.

The survey consists of eight sections. The first section collects demographic information such as age, gender, and university. In the following sections, 56 items measured seven primary constructs. The items were measured using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). For this study, a self-administered questionnaire was used, filled out independently by all participants. The data was collected through both online and offline methods. For the online approach, instructors received a link to an electronic copy of a questionnaire and emailed it to the students. The offline method involved a supporting letter from the researcher's supervisor introducing the study and assuring confidentiality and anonymity. The letter was sent to universities, and instructors facilitated data collection during lectures. All data were collected in Jordan during the summer semester of 2022/2023.

The Partial Least Square Path Model (PLS-PM) was the ideal method for this study due to its adaptability in exploring intricate relationships within a smaller sample size (Hair Jr et al., 2021). Its focus on predictive modelling, capacity to handle complex constructs, and suitability for non-normal data distributions makes it the optimal choice for unravelling the interplay of digital literacy, university support, personality traits and TPB factors in shaping DEI. Thus, the authors applied PLS-PM to assess the inner and outer relationships between several blocks of variables and to represent the blocks in a path diagram graphically (Chin, 1998; Wold, 1982). The PLS-PM procedure is a handy tool for constructing latent variables (LV) for each block. The model was built using 12 blocks identified through a multi-step procedure for constructing models. Some items were excluded from the model in step 1 because their factor loadings were less than 0.7. The reflective model was employed for index development, although both the formative model (Fornell & Larcker, 1981) and the reflective method of modelling LVs (Diamantopoulos, 1999) could be supported. The overall model fit was evaluated according to the Goodness-of-Fit (GOF) (Tenenhaus et al., 2004), standardized root mean square residual /SRMR/ (Hair Jr et al., 2021) and the root mean square residual covariance /RMR/ (Hair Jr et al., 2021). A bootstrapping was applied to validate the model parameters, according to Chin (1998). The mean and standard error of the estimates were calculated from 500 bootstrap samples. As a rule of thumb, the path coefficient can be considered significant if the standard error is less than half of the mean. Hence, standard errors and t statistics will also be reported together with the estimate. The GOF of 0.10; 0.25; 0.36 can be considered an adequate, moderate and good global fit (Wetzels et al., 2009). The thresholds for SRMR and RMR values are 0.08 and 0.12. Dillon Goldstein’s rho indices tested the composite reliability of the blocks. The identified dimensions should have reliability above the recommended 0.7 and most of the factor loadings should be greater than 0.7 (Hair Jr et al., 2021). R-squared values measured the assessment of structural model quality. According to Cohen (1988), the values of 0.02, 0.15, and 0.35 can be regarded as having small, medium, or significant effects. The model's discriminant validity was evaluated using the Fornell and Larcker criterion (1981). An LV's Average Variance Extracted (AVE) should always be greater than the variance in another latent construct that this LV contributes to explaining. All calculations were performed by R 3.4.4 software (*R. Core Team*, 2022) using the “plspm” package (Sanchez, 2013) and “olsrr” packages for the calculation of Variance Inflation Factor /VIF/.

EMPIRICAL RESULTS

The data consisted of 399 respondents and satisfied the sample size requirements proposed by leading authors in partial least squares (Hair Jr et al., 2021; Sanchez, 2013; Vinzi et al., 2010). The following blocks were examined on a 5-point Likert scale: DEI (5 items), ATE (5 items), SN (3 items), PBC (4 items), DL (9 items), PES (6 items), PCD (4 items), PBD (3 items), RT (4 items), LC (4 items), I (4 items), NA (5 items). Composite Reliability was measured by Dillon Goldstein's Rho value which was higher than 0.7 for all the latent variables indicating good composite reliability. Only those items were kept whose loading was greater than or around 0.7. For this reason, DEI1, ATE1, DL1 and DL6-9, PES4, RT3 and LC1 must be removed from the final model (Table 1 and 2). The model-building process and composite reliability assessment (loadings, Dillon Goldstein's Rho, VIF indices) can be seen in Table 1 and 2. Table 1 presents the main influential factors (ATE, SN, PBC, DL) on DEI.

Table 1. Composite Reliability of The Studied Items and Model Building I. [Source: Authors' Calculation.]

Item	Latent variable	Manifest variables	Loading before exclusion	Loading after exclusion	VIF (DEI)*	DG Rho/ AVE**
Online venture	Digital Entrepreneurial Intention (DEI)	DEI1	0.676		0.805	0.861 (60.4%)
Become a digital entrepreneur		DEI2	0.746	0.747	0.828	
Doubts		DEI3	0.681	0.697	0.873	
Digital company		DEI4	0.855	0.859	0.702	
Professional goal		DEI5	0.760	0.799	0.722	
More benefits	Attitude toward entrepreneurship (ATE)	ATE1	0.644		1.71	0.852 (59.9%)
Career		ATE2	0.767	0.749	2.06	
Start a firm		ATE3	0.714	0.744	1.70	
Great satisfaction		ATE4	0.808	0.838	2.14	
A good option		ATE5	0.742	0.763	1.86	
Approval of family	Subjective Norms (SN)	SN1	0.857	0.855	1.61	0.848 (70.6%)
Approval of friends		SN2	0.849	0.844	1.87	
Approval of peers		SN3	0.819	0.822	1.71	
Practical details	Perceived Behaviour Control (PBC)	PBC1	0.755	0.759	2.08	0.859 (60.7%)
Control of the process		PBC2	0.808	0.813	2.09	
Ease of operating a firm		PBC3	0.802	0.803	2.25	
High probability of success		PBC4	0.748	0.742	1.64	
Technical problems	Digital Literacy (DL)	DL1	0.505		1.67	0.854 (56.3%)
Different technologies		DL2	0.703	0.769	2.37	
Latest technologies		DL3	0.655	0.751	2.09	
Learn new technologies		DL4	0.669	0.743	1.75	
Technical skills		DL5	0.711	0.738	1.94	
Obtaining information from the internet		DL6	0.648		1.64	
Web-based activities		DL7	0.569		1.64	
ICT collaboration		DL8	0.560		1.72	
Obtain help		DL9	-0.168		1.26	

Note: *: Variance Inflation Factor (VIF) values should be lower than 5 in order to avoid multicollinearity; DEI: Digital Entrepreneurial Intention.**: Dillon Goldstein's Rho value and Average Variance Extracted.

Table 2 shows the other factors (Perceived University Support, Personal Traits) of the model.

Table 2. Composite Reliability of The Studied Items and Model Building II.
[Source: Authors' Calculation]

Item	Latent variable	Manifest variables	Loading before exclusion	Loading after exclusion	VIF* (ATE)	VIF* (PBC)	VIF* (DEI)	DG Rho/ AVE**
Elective courses	Perceived Educational Support (PES)	PES1	0.775	0.794			1.94	0.897 (60.0%)
Project work		PES2	0.772	0.807			2.50	
Internship		PES3	0.725	0.747			2.54	
Bachelor/master study		PES4	0.663				1.58	
Conferences/Workshops		PES5	0.769	0.748			2.09	
Contact with other students		PES6	0.761	0.774			3.10	
Career choice awareness	Perceived Concept Development (PCD)	PCD1	0.799	0.796			2.96	0.923 (72.2%)
Motivation for a new firm		PCD2	0.882	0.886			3.17	
Ideas to start a firm		PCD3	0.863	0.862			3.47	
Knowledge to start a firm		PCD4	0.851	0.854			3.73	
Financial means	Business Development Support (BDS)	BDS1	0.853	0.850			2.65	0.913 (69.0%)
Reputation support		BDS2	0.763	0.755			2.98	
Lead customer		BDS3	0.869	0.881			2.97	
Higher risks for higher returns	Risk-Taking propensity (RT)	RT1	0.774	0.799	1.58	1.58	1.78	0.836 (64.3%)
New riskier experiences		RT2	0.831	0.844	1.79	1.79	2.00	
Risk of failure is not a concern		RT3	0.634		1.38	1.38	1.57	
High returns over security		RT4	0.735	0.760	1.40	1.40	1.64	
Behaviour control	Locus of Control (LC)	LC1	0.631		1.33	1.33	1.49	0.771 (57.2%)
Plans will be realized		LC2	0.742	0.766	1.51	1.51	1.62	
Self-awareness		LC3	0.732	0.762	1.33	1.33	1.54	
Personal commitment		LC4	0.709	0.741	1.24	1.24	1.45	
Novel ideas	Innovativeness (I)	I1	0.703	0.700	1.61	1.61	1.79	0.855 (59.9%)
Creative thinking		I2	0.778	0.783	1.86	1.86	2.26	
Help in creative activities		I3	0.790	0.790	1.62	1.62	2.00	
Original ideas		I4	0.821	0.820	1.69	1.69	1.92	
Success in work	Need for Achievement (NA)	NA1	0.753	0.752	1.87	1.87	2.29	0.898 (66.1%)
Master of things		NA2	0.858	0.857	1.94	1.94	2.20	
Do the very best		NA3	0.787	0.786	1.88	1.88	2.10	
More successful than others		NA4	0.830	0.828	2.00	2.00	2.22	
Targets above standards		NA5	0.833	0.837	2.37	2.37	2.62	

Note: *: Variance Inflation Factor (VIF) values should be lower than 5 to avoid multicollinearity; ATE: Attitude Toward Entrepreneurship; PBC: Perceived Behaviour Control; DEI: Digital Entrepreneurial Intention. **: Dillon Goldstein's Rho value and Average Variance Extracted (in %).

DEI was best described by intention to start a digital company (0.859), ATE was best represented by great satisfaction (0.838), and the main item on PBC was the control of the process (0.813). Among DL items, technology-related items were the most influential. PES was best described by elective courses (0.794) and project work (0.807), BDS was best related to financial means (0.850) and lead customer status of the university (0.881). RT was about taking new, riskier experiences (0.844), while Innovativeness depended mostly on original ideas (0.821). NA was well defined by being a master in all things (0.858) and reaching targets above standards (0.833).

Figure 2 shows the graphical model, the parameter estimates and R-squared values from the bootstrap validation. The PLS-PM model is an iterative and explanatory technique; therefore, it can identify irrelevant relationships. For better understanding, only the statistically significant path coefficients were depicted and dashed lines denoted non-significant paths. All given values were significant at a 5 per cent significance level.

The overall model had a good global fit as the GOF was 0.428, and the SRMR was 0.053 (the threshold is 0.08), while the RMR was 0.118 (the threshold is 0.12). The primary outcome variable, DEI, had the largest R2 value (0.495, SE=0.049; t=11.17; p<0.001) but the prediction of the secondary outcomes, PBC and ATE, also had substantial R2 value (0.253; SE=0.032; t=6.63; p<0.001 and 0.238; SE=0.037; t=6.63; p<0.001). The strongest relationship could be seen between ATE and DEI (B=0.522; SE=0.046; t=11.35; p<0.001) and between RT and PBC (B=0.252; SE=0.057; t=4.42; p<0.001) and between I and PBC (B=0.214; SE=0.061; t=3.51; p<0.001). Results suggested that a higher level of PBC and ATE increased the DEI and RT, and I boosted PBC. See Figure 2 below, which shows the PLS-SEM model.

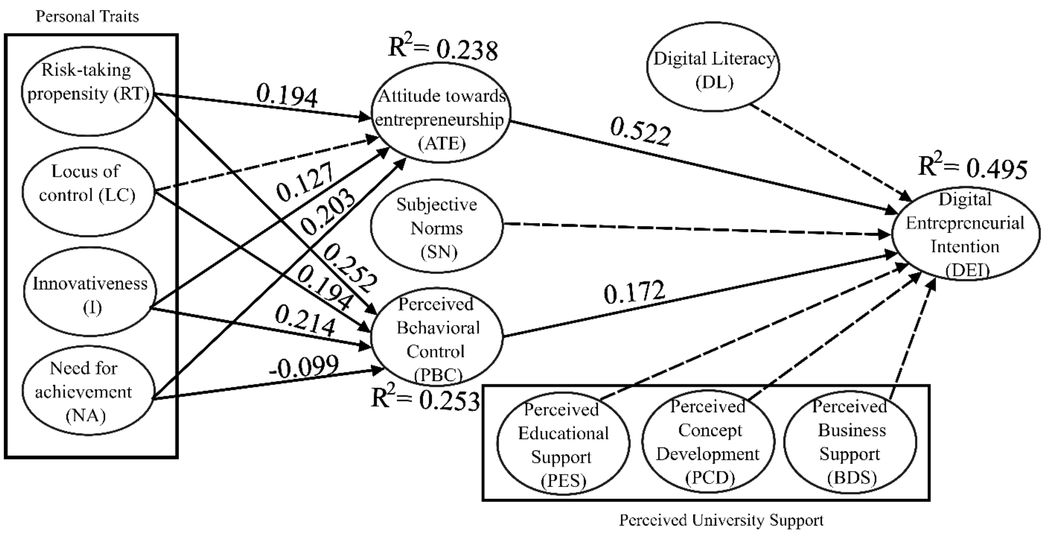

Figure 2. The PLS-SEM Model
[Source: Authors' Design]

On the other hand, NA had a positive influence on ATE (B=0.203; SE=0.056; t=3.63; p<0.001) and a negative effect on PBC (B=-0.099; SE=0.047; t=-2.11; p=0.035). Also, LC only impacted PBC (B=0.203; SE=0.071; t=2.86; p=0.005). I and RT also had a weaker but significant effect on ATE ($B=0.127$; $SE=0.059$; $t=2.15$; $p=0.032$ and $B=0.194$; $SE=0.057$; $t=3.40$; $p<0.001$). On the other hand, LC did not affect ATE and NA didn't affect PBC.

DISCUSSION

A strong and positive relationship have been found between ATE and DEI in great balance with previous studies (Aleidi & Chandran, 2019; Anwar et al., 2021). Our findings revealed that internal factors seem more influenced by students' entrepreneurial intentions than external ones, like social norms (Farani et al., 2017). PBC is positively related to DEI which is aligned with previous studies (Hassan, 2020; Karimi et al., 2017). Surprisingly, DL had no significant effect on DEI that contradicted previous studies reporting a positive correlation between the two factor (EL-SISI, 2022; Hardika et al., 2022). The reason might be that over half of Jordanians aged 24 or younger have grown up amid a notable technological revolution; they are highly connected, educated, and globally aware, poised to be digitally literate (Innovative Jordan, 2017). This generation includes university students often perceived as digital natives and technologically savvy (Kulikowski et al., 2022). DL may not directly influence the intention to engage in digital entrepreneurship, but it still plays a crucial role in pursuing entrepreneurial activities.

The findings suggested that students' experience with university support conditions had not spurred their desire to start a business. As a result, we found that entrepreneurship university support in Jordan universities does not adequately inform students of entrepreneurship as a career choice. These findings are consistent with previous research (Ambad & Damit, 2016). Prior research has demonstrated that personality traits can impact entrepreneurial behavior and intentions, either directly or indirectly (Biswas & Verma, 2021; Munir et al., 2019). According to the model derived from the TPB and expanded upon here, exogenous personality characteristics indirectly and positively influence DEI through motivational antecedents ATE and PBC (Liñán & Chen, 2009). RT directly and significantly impacted ATE and PBC which was aligned with previous studies (Anwar et al., 2021; Karimi et al., 2017). Our results showed that LC had no significant effect on ATE, paralleled with (Younis et al., 2020). It also positively and significantly affected PBC (Karimi et al., 2017; Shimoli et al., 2020). On the other hand, Innovativeness showed a positive and significant effect on both ATE and PBC, which can be confirmed by previous studies (Anwar et al., 2021; Karimi et al., 2017). The last personality trait was Need for achievement (NA), which represented the desire to excel, accomplish complex tasks, and surpass others in performance. Our results found that NA positively impacted ATE, parallels with (Younis et al., 2020). It also negatively impacted PBC, agreeing with an earlier study (Shimoli et al., 2020).

This study exhibits several limitations. Firstly, its scope is restricted to undergraduate business students in Jordan, thus constraining the applicability of the results to other student populations or diverse contexts. Future investigations could enhance comprehensiveness by incorporating students from varied disciplines, educational levels, and regions to understand digital entrepreneurship intentions better. Secondly, the study's cross-sectional design hinders establishing causal relationships between the variables under examination and digital entrepreneurship intention. Utilizing longitudinal designs in future research may yield more robust evidence of causality and illuminate the dynamic nature of these relationships over time.

Thirdly, using a quota sampling method may introduce selection bias, resulting in a sample that only partially reflects the broader population of undergraduate business students in Jordan. Lastly, the study's reliance on a relatively small sample size of 399 students may compromise the analysis's statistical power, limiting the findings' precision and reliability. Therefore, caution is advised in interpreting and applying the study's results. Subsequent research endeavors with more extensive and diverse samples are warranted to validate and broaden the current findings.

CONCLUSIONS

This study explored the factors influencing digital entrepreneurship intention (DEI) among undergraduate business students in Jordan. The findings indicate that DEI is positively influenced by attitude towards entrepreneurship (ATE). At the same time, subjective norms (SN) did not significantly influence DEI, suggesting that entrepreneurs rely more on internal drive and support than social support. Perceived behavioral control (PBC) was positively related to DEI, suggesting that students perceived to have the necessary skills and resources were more likely to engage in digital entrepreneurship. On the contrary, digital literacy and perceived university support did not significantly affect DEI, indicating a need for tailored entrepreneurship support for Jordanian students. Personality traits, such as risk-taking propensity, locus of control, innovativeness, and need for achievement, also showed varying effects on ATE and PBC with an indirect influence on DEI. The Government of Jordan has been taking significant steps to foster digital entrepreneurship, such as establishing technology parks, incubators, and accelerators have been launched to provide a supportive ecosystem for digital entrepreneurs.

However, despite these efforts, universities must align their curriculum, research, and support services with the demands and opportunities of digital entrepreneurship. By enhancing collaboration between the government, industry, and higher education, universities can play a vital role in equipping students with the necessary knowledge, skills, and resources to thrive in the digital economy and contribute to the growth of digital entrepreneurship in Jordan. The authors concluded that internal psychological factors could significantly and directly shape perceived behavior control and the attitude towards entrepreneurship among the students facilitating the start of a digital business. Based on the authors' experience, university support as an external environment can help develop internal factors.

THE THEORITICAL AND PRACTICAL IMPLICATIONS

The implications are transformative at a policy level, urging university support structures for entrepreneurial students to recalibrate. It emphasizes the need for a comprehensive approach, including theoretical knowledge, guidance, mentorship, and resources to empower students in digital entrepreneurship. The study highlighted the importance of personality traits in digital entrepreneurship and emphasized the need for tailored personality development programs. Educational institutions can facilitate the emergence of well-rounded, confident digital entrepreneurs. In conclusion, the study advanced the understanding of digital entrepreneurial intention among Jordanian students and laid the groundwork for an ecosystem that nurtures innovation and economic growth.

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ICT ADOPTION BY MOMPRENEURS DURING THE COVID-19 PANDEMIC: THE ROLE OF ENTREPRENEURIAL ORIENTATION

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Abstract: *Information and Communication Technologies (ICTs) can benefit mompreneurs, empowering them to start and expand their business. ICTs became even more important for mompreneurs during the COVID-19 pandemic when small business owners had to reinvent themselves and seek alternative ways of maintaining their sales and remaining in the market. In this context, this paper aims to investigate factors related to ICT adoption by Brazilian mompreneurs. The data were collected during the first months of COVID-19 pandemic and were analyzed through structural equation modelling. The descriptive analysis shows that mompreneurs are adopting innovative technologies such as electronic payments, cloud computing, social networks, video conferencing, and others to manage their business. Moreover, the results indicate that two dimensions of Entrepreneurial Orientation (proactiveness and risk-taking) have a significant effect on perceived ease-of-use and an indirect effect on ICT adoption.*

Keywords: *Mompreneurship, Entrepreneurial Orientation, ICT Adoption, COVID-19.*

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INTRODUCTION

The increasing technological advances inherent to the digital age have revolutionized the ways of creating and doing business (Choudrie & Vyas, 2014; Wamuyu, 2015; Kraus et al., 2019). As indicated by Mathew (2010), Information and Communication Technologies (ICTs) tools help entrepreneurs in several areas such as product development, strategic planning, and marketing in addition to creating knowledge and expanding communication possibilities. Furthermore, cutting-edge technologies such as artificial intelligence, virtual reality, and big data analytics can provide significant benefits to business by improving the customers' experience and, consequently, increasing their satisfaction (Ameen, Hosany & Tarhini, 2021; Ameen, Tarhini, Reppel & Anand, 2021).

ICTs are especially relevant for mompreneurs that, aiming to balance the roles of mother and entrepreneur, usually operate their businesses from home, depending on ICTs to succeed and grow (Costin, 2011). ICTs facilitate the activity of mompreneurs during the last months of pregnancy and the first months after the baby is born, when women's physical movements are more restricted (Richomme-Huet & Vial, 2014). However, studies reveal that women often face barriers such as limited financial capital to invest in ICTs and lesser access to IT training opportunities (Orser et al., 2019), which may restrict their access to cutting-edge technologies. In this context, Internet-based technologies such as social media and e-commerce platforms can compensate for these limitations, by providing the conditions for mompreneurs to start a business and to establish a flexible schedule that fits their family responsibilities (Richomme-Huet & Vial, 2014; Orser et al., 2019).

During the COVID-19 pandemic, ICTs became even more important for the enterprises. Kim (2020) highlights the acceleration of digital transformation in the market during this period and Rapaccini et al. (2020) emphasize that in periods of calamity such as the COVID-19 pandemic, firms need to become more resilient and less dependent on human interactions by introducing new technologies and digital offerings. Brazil is one of the countries that was most affected by the COVID-19 pandemic (Farias & Araújo, 2021). The first case was registered in Brazil in February 2020 (Brazil, 2021) and since then, several restrictive measures have been taken by city mayors and state governors to contain the spread of the virus, such as social distancing, mandatory use of masks and closure of retail stores, malls, restaurants, hair salons etc.

In this scenario, this paper aims to investigate factors related to ICTs adoption by Brazilian mompreneurs through an extended Technology Acceptance Model (TAM) approach. According to Zaremohzzabieh et al. (2016), in order to understand ICTs adoption in small business, it is important to extend TAM with latent factors of entrepreneurship. A factor that is closely related to entrepreneur's activities and that differs among women and men (Adams et al., 2017; Zimmerman & Brouthers, 2012) is entrepreneurial orientation. Thus, in this paper we have extended TAM with the dimensions of Entrepreneurial Orientation (proactiveness, innovativeness, and risk-taking).

As pointed by Adams et al. (2017), focusing on women from developing countries is important due to the relevant role that entrepreneurship plays for the empowerment of women in these countries. Furthermore, women-owned businesses were the most affected by the COVID-19 pandemic (Manolova et al., 2020). Finally, the main results of this paper have the potential to extend TAM with the dimensions of Entrepreneurial Orientation (proactiveness, innovativeness, and risk-taking). By incorporating individual Entrepreneurial Orientation to TAM, this study attempts to provide a broader representation of the factors affecting mompreneurs acceptance of information technologies.

LITERATURE REVIEW

Recognized as a key factor for socioeconomic development of growing economies, female entrepreneurship helps women to expand their participation in the labor market, contributing to reduce inequalities and poverty (Mathew, 2010; Sarfaraz, Faghih & Majd, 2014). Considered a little studied phenomenon in the literature, mompreneurship can be viewed as a dimension of female entrepreneurship, given the particularity of being driven by the desire to balance the roles of mother and entrepreneur (Richomme-Huet and Vial, 2014). Richomme-Huet and Vial (2014) point out that motherhood encourages self-employment due to the family responsibilities imposed to mothers. According to the authors, it is common for mothers to leave the formal labor market and start a business activity as an alternative source to supplement the family income.

The study of Ajefu (2019) identified that having children increases women's probability of being entrepreneur. As pointed by Ajefu (2019), childcare requires intensive efforts of women, affecting their performance in the formal labor market and leading then to seek for a self-employment that provides them with flexible working hours and the possibility of balancing the relationship between work and childcare. Flexible work is also pointed out by Genç and Oksuz (2015) as an emerging feature in the business environment that provides women with greater participation in the labor market, despite their family responsibilities. The concerns with the household and well-being of children were pointed by Janssens et al, (2019) as women's motivation for the implementation of their own business.

Regarding ICTs adoption, previous studies show that women entrepreneurs have been using technological innovations as an instrument of business development (Mathew, 2010; Beninger et al., 2016; Gichuki & Mulu-Mutuku, 2018; Crittenden et al., 2019). These studies highlight the role of technology as an effective tool for women entrepreneurs, since ICTs contribute to: empower women; expand their business; build reputation and social capital; increase marketing reach; create competitive advantage; and explore opportunities in the global market (Mathew, 2010; Costin, 2011; Beninger et al., 2016; Gichuki & Mulu-Mutuku, 2018; Crittenden et al., 2019).

With regard to mompreneurship, Costin, (2011) points that ICTs enable mompreneurs to develop their business activities at home. However, considering the lack of empirical research related to technology adoption by mompreneurs, Costin (2011) points out the need of empirical studies to investigate mompreneurs that have adopted ICTs and that have succeeded in their business. According to the author, the results of these studies can be used to build a database containing the main practices that resulted in positive outcomes (Costin, 2011). Thus, this study aims to fill this gap in the literature.

RESEARCH MODEL AND HYPOTHESES

Technology Acceptance Model

Among the theories to investigate user acceptance of technologies, the Technology Acceptance Model (TAM) proposed by Davis (1989) has been the most employed in the Information Systems literature (Ayeh, 2015; Zaremohzzabieh et al., 2016). It postulates that the acceptance of a new information system is predicted by two variables: the perceived usefulness and the perceived ease of use (Davis, 1989). According to Davis (1989), ease of use means that the system is free from difficulty to be used. A useful system is the one that enhances user-performance (Davis, 1989).

The TAM also posits that perceived ease of use impacts perceived usefulness. This means that if a system is perceived as useful and relevant to the performance of the user's activities, but it is perceived as difficult to use, it may not be adopted (Davis, 1989). The TAM has been used to investigate user acceptance of different Information and Communication Technologies (ICTs) such as Near Field Communication (NFC) (e.g. Dutot, 2015), Mobile Banking (e.g. Malaquias & Silva, 2020), automated vehicles (e.g. Zhang et al., 2020), and social media (e.g. Gavino et al., 2019). In the context of female entrepreneurship, Crittenden et al. (2019) have used TAM to examine the impacts of ICTs adoption on social capital, self-efficacy, and empowerment.

Prior studies have confirmed empirically that new technologies tend to be adopted when individuals perceive them as easy to use and useful, and that perceived ease of use have a positive effect on perceived usefulness (Crittenden et al., 2019; Malaquias & Silva, 2020; Zhang et al., 2020). Based on these previous studies we hypothesized that:

H1a: Perceived usefulness has a positive effect on ICTs adoption by mompreneurs
H1b: Perceived ease of use has a positive effect on ICT adoption by mompreneurs.
H1c: Perceived ease of use has a positive effect on perceived usefulness.

Although Davis (1989) have identified that perceived ease of use and perceived usefulness are key determinants of technology acceptance, he emphasized the need of future research to examine how other variables impact usefulness, ease of use, and technology acceptance. Therefore, several studies have proposed the extension of TAM, by incorporating other variables (Dutot, 2015; Malaquias & Silva, 2020; Zhang et al., 2020; Gavino et al., 2019; Crittenden et al., 2019). In order to apply the TAM in the context of mompreneurship we have extended TAM with the dimensions of Entrepreneurial Orientation: innovativeness, proactiveness, and risk-taking propensity.

Entrepreneurial Orientation

Entrepreneurial orientation (EO) is related to the behavior of managers, involving aspects such as their practices and decision-making process (Tajudeen, Jaafar, & Ainin, 2018). Previous studies have indicated that EO is one of the factors driving the diffusion and adoption of innovations by entrepreneurs (Peltier et al., 2009; Gupta et al., 2016; Eggers et al., 2017; Dubey et al., 2020).

Gupta et al. (2016) argue that EO is a psychological construct that may impact new technologies adoption and point that EO may increase the probability that an individual will adopt and have a sustained engagement with new technologies. According to Eggers et al. (2017), EO is a factor that influences social media use and Dubey et al. (2020) pointed that EO is closely related to the adoption of big data analytics.

EO consists of three major dimensions: innovativeness, proactiveness, and risk-taking (Abebe, 2014; Rigtering et al., 2014; Tajudeen, Jaafar & Ainin, 2018). Unlike previous studies that analyzed the impact of EO on technology adoption considering it as a single construct, in the present study we considered and tested each dimension of EO as an independent variable in the same way as Hammerschmidt et al. (2020).

Innovativeness can be viewed as a propensity to engage in new ideas, creative process, experimentation, and technological leadership (Abebe, 2014; Rigtering et al., 2014). The study of Thong and Yap (1995) showed that there is a positive relation between CEOs innovativeness and IT adoption in small business. Magotra et al. (2016) also found that innovativeness is a key factor affecting technology adoption.

Proactiveness involves the behaviors of taking the initiative and acting in anticipation of future problems, trends and demands (Abebe, 2014; Rigtering et al., 2014). According to Abebe (2014), a high level of proactiveness among small business owners/managers can lead to e-commerce adoption. The study of Dubey et al. (2020) revealed that proactiveness is one of the desirable entrepreneurial traits when making decisions related to new technologies adoption.

Risk-taking reflects the disposition of entrepreneurs to engage in projects that have uncertain results or high probability of failure (Rigtering et al., 2014; Tajudeen, Jaafar & Ainin, 2018). Peltier et al. (2009) identified a positive relationship between risk orientation and adoption of CRM and the study of Quinton et al. (2018) indicates that risk taking propensity is a determinant of a Digital Orientation. Magotra et al., (2016) found that risk-taking propensity have positive impact on disposition of individuals towards technologies adoption. Abebe (2014) argues that entrepreneurially oriented firms are more likely to take risks in adopting new technologies, such as e-commerce, aiming to improve their business performance and competitiveness in the market.

As pointed by Pipitwanichakarn and Wongtada (2019), although innovativeness, risk-taking and proactiveness behaviors entail a sense of technology readiness, EO may not have a direct impact on technology adoption, since factors such as trust, ease of use, and perceived usefulness mediate this relationship. Furthermore, Venkatesh and Davis (2000) point that that effect of external factors on usage behavior is mediated by perceived ease of use and perceived usefulness. Based on the study of on Venkatesh and Davis (2000) and on Pipitwanichakarn and Wongtada (2019), we argue that the linkage between the dimensions of EO and ICT adoption is indirect with ease of use and perceived usefulness mediating this relationship. Therefore, we proposed the following hypotheses:

H2a: Innovativeness has a positive effect on perceived ease of use.
H2b: Proactiveness has a positive effect on perceived ease of use.
H2c: Risk-taking propensity has a positive effect on perceived ease of use.

Figure 1 presents the research model and the hypotheses of the study.

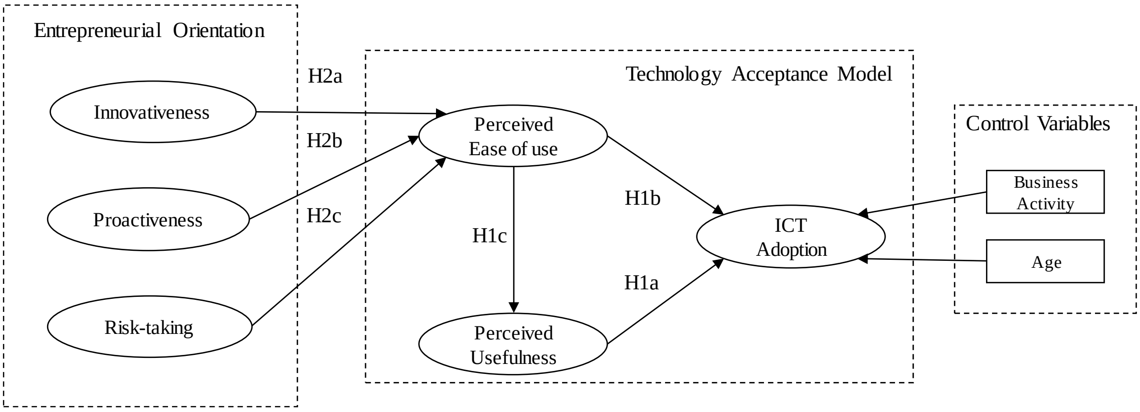

Figure 1. Research Model.

METHODS

In order to achieve the purpose of this research, we collected data through an online survey. The questionnaire, which was answered in a voluntary and anonymous way by the participants, was developed based on a literature review and contains questions pertinent to the research's objective, such as demographic characteristics, respondents' perception about ICTs adoption, and entrepreneurial orientation. The Appendix shows the items and references that we used for the constructs Ease of Use, Perceived Usefulness, Innovativeness, Proactiveness, and Risk-taking. For these items, we used a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5).

Initially, we invited mompreneurs from our contact lists at social networks to participate in the research. Then, we used a snowball sampling technique to identify mompreneurs outside of those lists, asking the initial participants to indicate other mompreneurs who could participate in the research. The data collection occurred from April 2020 to June 2020, which correspond to the first months of COVID-19 pandemic.

After obtaining the responses, we examined the data and excluded questionnaires with missing values, straight lining responses and questionnaires that did not meet the inclusion criteria of the research. Some respondents, for example, indicated that they didn´t have any children.

Overall, there were 176 complete and valid questionnaires available for data analysis. As recommended by Hair et al. (2019), the minimum sample size for models with less than seven constructs, at least modest communalities (.5), and no underidentified constructs is 150. Hair et al. (2019, p. 632) also points that the Maximum Likelihood Estimation (MLE) used in this paper, "provides valid and stable results for simple models with sample sizes as small as 50". Furthermore, for the factor analysis, it is recommended a ratio of at least 5 participants per item (Tinsley & Tinsley, 1987; Hair et al., 2019). Since the questionnaire has 19 items, 95 participants would suffice.

We analyzed the data through descriptive statistics and, then, we conducted the evaluation of the research model in two stages (Anderson & Gerbing, 1988). First, the indicators of the Confirmatory Factor Analysis - CFA (convergent and discriminant validity) were accessed. After the CFA, we used Structural Equation Modeling (SEM) for hypothesis testing. For the CFA, as well as for the SEM, we observed the guidelines available in the literature (Hair et al., 2005). In order to analyze a potential indirect effect of Entrepreneurial Orientation Dimensions on ICT

Adoption, we also observed the bootstrap confidence intervals (in this case, we considered 2,000 bootstrap subsamples). To include Age as a control variable, we have converted it in a categorical variable (1 = 20 - 29 years old; 2 = 30 - 39 years old; 3 = 40 - 49 years old; 4 = 50+ years old). The control variable Business Activities is a dummy variable with 1 representing “products selling” and 0 representing “service firms”.

RESULTS

Table 1 presents the demographic data of the mompreneurs that participated in the survey. The results in Table 1 indicate that the sample was comprised of mompreneurs of different ages, level of education, and marital status. It is important to note that most of the respondents have completed at least the undergraduate level.

A descriptive analysis of the dataset also reveals that in addition to running their own business, approximately 25% of the respondents have another job and that 40% of the respondents are the main responsible for the household income. Moreover, almost 50% of the mompreneurs have formal business activities, but less than 25% of them have employees. About 60% of them sell products (food, cosmetic products, clothes and accessories, for example) and 40% operate in the service sector (insurance, health, education, architecture, beauty services etc.). The sample profile is similar to the sample profile of the research of Crittenden et al., (2019) carried out with women entrepreneurs in South Africa.

Table 1. Demographic characteristics of the respondents

Age	**n**	**%**	**Number of children**	**n**	**%**
20-29	11	6.25	1	71	40.34
30-39	63	35.80	2	81	46.02
40-49	63	35.80	3+	24	13.64
50+	39	22.16	**Level of Education**	**n**	**%**
Marital Status	**n**	**%**	Some primary school	3	1.70
Single	21	11.93	Some high school	2	1.14
Married or living together	130	73.86	High school	24	13.64
Divorced or Separated	16	9.09	Some university work completed	17	9.66
Widowed	7	3.98	Undergraduate degree completed	48	27.27
Missing	1	0.57	Graduate degree completed	79	44.89

Source: own elaboration.

Table 2 shows an overview of the ICTs adopted by the mompreneurs. In line with the research of Crittenden et al., (2019), almost all of the mompreneurs that participated in the research (97.73%) use WhatsApp to support their business activities. Facebook and Instagram are also used by most of them. These data are also similar to those of previous studies carried out with women entrepreneurs, such as the study of Jose (2018), which showed that Facebook and WhatsApp were the most popular platforms for women entrepreneurs in the United Arab

Emirates, and the study of Choudhury (2021), that found that Instagram and Facebook are the main social media adopted by Bangladeshi women.

As reported in Table 2, more than 97% of the respondents use smartphones to support their business, while notebooks are used by close to 70% of them. These results are also similar to those of Crittenden et al. (2019) and reflect the popularity of smartphones in developing countries such as Brazil, showing that, in addition to personal use, smartphones are broadly used for business administration.

About 25% of the respondents indicated that they use other types of ICTs such as e-commerce platforms, cloud computing, video conferencing, financial management systems, CRM systems and image editing software.

Table 2. Social media and devices used by the respondents.

Social Media	n	%	Device	n	%
WhatsApp	172	97.73	Smartphone	171	97.16
Instagram	143	81.25	Notebook	122	69.32
Facebook	138	78.41	Desktop Computer	54	30.68
Youtube	39	22.16	Tablet	28	15.91
LinkedIn	23	13.07			
Twitter	10	5.68			
Other	19	10.80			

Note: More than one Social Media and Device could be selected by the respondent.
Source: own elaboration.

In order to evaluate the internal consistency and convergent validity of the constructs, we used the following indicators: Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha (CA). According to the literature, these indicators must be higher than 0.5, 0.7, and 0.7, respectively (Hair et al., 2005). The results in Table 3, show that all indicators meet these criteria, indicating that the constructs present good reliability and convergent validity.

Table 3. Constructs reliability and internal consistency.

Construct	AVE	CR	CA
PU	0.858	0.947	0.944
PEOU	0.717	0.883	0.878
Innovativeness	0.652	0.847	0.834
Proactiveness	0.528	0.769	0.754
Risk-taking	0.636	0.839	0.834
ICT Adoption	0.755	0.924	0.921

Source: own elaboration.

Regarding to discriminant validity, the root square of the AVE for each construct must be higher than the correlations of the construct with other constructs. Table 4 presents these statistics and shows that, for all constructs, the observed values satisfy this specification.

In summary, the results indicate that the constructs have good internal consistency (Table 3) and represent individual measures (Table 4).

Table 4. Discriminant Validity

Construct	PU	PEOU	Innovat.	Proact.	Risk-tak.	ICT Adop.
PU	**0.926**					
PEOU	0.491	**0.847**				
Innovat.	0.129	0.275	**0.808**			
Proact.	0.502	0.393	0.573	**0.726**		
Risk-tak.	0.229	0.400	0.335	0.522	**0.797**	
ICT Adop.	0.661	0.528	0.096	0.386	0.205	**0.869**

Note. Diagonal values represent the square roots of AVE; off-diagonal values represent the correlation between the constructs.
Source: own elaboration.

In the CFA stage we also analyzed the indexes for goodness of fit. Table 5 displays the observed statistics for our measurement model. This table also contains the indexes related to the structural model that was used for hypotheses testing with SEM. Both CFA and SEM analysis presented measures for goodness of fit higher or close to the values suggested by the literature.

Table 5. Goodness of fit of the models.

Items	CFA	SEM
RMSEA	0.069	0.085
RMSEA (LO 90)	0.055	0.074
RMSEA (HI 90)	0.082	0.096
Chi-square	250.673	410.869
d.f.	137	183
Chi-square/d.f.	1.830	2.245
GFI	0.873	0.816
IFI	0.953	0.904
CFI	0.953	0.903

Notes. d.f.: degrees of freedom; RMSEA: Root Mean Square Error of Approximation; GFI: Goodness of Fit Index; IFI: Incremental Fit Index; CFI: comparative fit index.
Source: own elaboration.

After the CFA, we started the hypotheses testing. Table 6 shows the expected signs for the hypotheses and the path coefficients. The r-squared for the main dependent variable (ICT Adoption) was 0.524, which means that the variables can explain about fifty-two percent of the variance of ICT adoption.

Table 6. Results of the hypotheses testing.

Hyp.	Relationship	Expected sign	Path Coefficients	Result
H1a	PU → ICT Adoption	+	0.612 ***	Supported
H1b	PEOU → ICT Adoption	+	0.282 ***	Supported
H1c	PEOU → PU	+	0.457 ***	Supported
H2a	Innovativeness → PEOU	+	0.082	Not Supported
H2b	Proactiveness → PEOU	+	0.234 ***	Supported
H2c	Risk-Taking → PEOU	+	0.238 ***	Supported

Note: ***: p<0.01.
Source: own elaboration.

The effect of the control variables Business Activity and Age on ICTs adoption was not significant. This means that the adoption of technologies occurs regardless of the sector in which the mompreneur operates and that age does not represent a barrier to technology adoption by mompreneurs.

The findings also show that PEOU was strongly predicted by the dimensions of proactiveness and risk-taking, but was not necessarily predicted by innovativeness (see Table 6). The variables Proactiveness and Risk-Taking presented a positive and significant indirect effect on ICTs adoption through Ease of Use and through Perceived Usefulness ($p<0.01$ for Proactiveness and $p<0.05$ for Risk-Taking). Moreover, these two variables (Procatciveness and Risk-Taking) also presented a significant positive indirect effect on Perceived Usefulness through the construct Ease of Use ($p<0.01$ and $p<0.05$, respectively). The results are consistent with the TAM theory that posits that the effect of external factors on usage behavior is mediated by perceived ease of use and perceived usefulness (Venkatesh & Davis, 2000). The findings are also in line with the findings of Pipitwanichakarn and Wongtada (2019), that found that the effect of EO on ICT adoption is indirect.

The results indicate that behavioral characteristics of mompreneurs (proactiveness and risk-taking) have a positive effect on technology adoption. Considering that the data were collected during the first months of the COVID-19 pandemic, the findings suggest that these behaviors are important for mompreneurs to keep up with the acceleration of digital transformation in the market during this period. Although mompreneurs who are less inclined to take risks and that are less proactive have chosen to develop entrepreneurial activities, they may be benefiting less from ICTs resources due to behavioral barriers.

Considering the relevance of the mompreneurship to the socioeconomic development, the main results of this study reinforce the need of public policies and initiatives aimed at enhancing mompreneurs self-efficacy to use ICTs. As perceived ease of use proved to be a determining factor in the adoption of ICTs by mompreneurs, policymakers can, for example, offer specialized training programs to mompreneurs. As pointed by previous studies, ICTs adoption can lead to greater marketing reach, empowerment and better business performance (Mathew, 2010; Costin, 2011; Beninger et al., 2016; Gichuki & Mulu-Mutuku, 2018; Crittenden et al., 2019). By knowing the potential of ICTs and by understanding how to use them, these women can expand their perception on the usefulness of ICTs and feel more prepared to use them. Thus, this study has practical implications because it offers insights that can help mompreneurs to understand the application of information technologies and their importance to business. This is especially significant for developing countries like Brazil, which has a large number of women entrepreneurs who can benefit from low-cost technological resources such as social media.

CONCLUSIONS

Considering the relevant role that Information and Communication Technologies (ICTs) play in the context of mompreneurship, this study investigated factors related to ICTs adoption by mompreneurs during the COVID-19 pandemic, by extending TAM with the dimensions of entrepreneurial orientation.

The results show that perceived usefulness and perceived ease of use are positively related to ICTs adoption. Furthermore, we identified that two entrepreneurial orientation dimensions (risk-taking and proactiveness) have positive and significant effect on perceived ease of use and an indirect effect on ICTs adoption. Mompreneurs who present behavioral characteristics related to proactiveness and risk-taking are more likely to adopt technological tools that may contribute to their business development. These findings indicate that behavioral factors can influence technology adoption by entrepreneurs even during periods of crisis when digital acceleration is of fundamental importance.

We also found that smartphones and WhatsApp are used by almost all respondents to support their business activities. Facebook and Instagram are also used by most of them. The usefulness and ease of use of these technologies for business administration purposes and the fact that they are free tools may be related to their diffusion and acceptance among the mompreneurs. It is important to highlight the role that these technologies play in empowering these women by allowing them to work from home, balancing the family responsibilities with their entrepreneurial activities. Through social network marketing, it is possible for mompreneurs to follow market trends to offer to customers exactly what they want. Anticipating customer aspirations can become an interesting technique to increase the sales. It is also important to emphasize the resources provided by social media such as Instagram that allow mompreneurs to implement digital offerings in an innovative way.

Electronic payment, that can help these women to expand their market, is an innovative technology that is being adopted by most of the respondents. The study also reveals that most mompreneurs use ICTs to learn how to increase their sales and to present products and services to the customers. Finally, we identified that, in addition to social networks, 25% of the respondents use other types of ICTs to manage their business, which includes cloud computing, e-commerce platforms, video conferencing, financial management systems, CRM tools and image editing software.

We emphasize the necessary adaptation experienced by these women during the COVID-19 pandemic, a scenario that have accelerated the digital transformation and required the development of new business strategies. Thus, the mompreneurs that participated in the research may have found in ICTs an alternative to manage and maintain their business.

This research has practical and theoretical contributions. From the theoretical point of view, this study contributes to the literature by extending the TAM with the dimensions of entrepreneurial orientation and by demonstrating that the propensity to behave entrepreneurially is an important factor to understand business owners' reactions to ICTs. The findings of the study reinforce the relevance of considering behavioral factors in addition to technological constructs to achieve a more comprehensive understanding of technology adoption. Moreover, this research contributes to fill the gap related to the lack of studies on ICTs adoption in the context of mompreneurship.

Regarding the practical contributions, this study reflects the perception of mompreneurs from a developing country regarding ICTs adoption; entrepreneurship is of especial relevance in these countries and the main findings of this research can contribute to the development of public policies and initiatives aimed at these businesswomen. These policies and initiatives would be especially relevant for mompreneurs that are less inclined to take risks and may empower them to face competitive challenges.

This study is pioneering in investigating ICTs adoption by mompreneurs. Future studies can test the proposed model with mompreneurs from other developed and developing countries to make cross-country comparisons, since the national level of income may be one of the factors that influence the adoption of ICTs by mompreneurs. Future research can also investigate how cultural factors affect ICTs adoption by mompreneurs in developing and developed countries. Finally, further studies could investigate the impacts of ICTs adoption in the context of mompreneurship.

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Appendix

Perceived Ease of Use (Davis, 1989; Crittenden et al., 2019)
EU1 - Overall, I find ICTs easy to use to support my business
EU2 - Learning to use ICTs would be easy for me
EU3 - I feel comfortable using ICTs to support my business

Perceived Usefulness (Davis, 1989; Crittenden et al., 2019)
PU1 - I find ICTs useful in supporting my business
PU2 - Using ICTs enhances my business effectiveness
PU3 - Using ICTs improves my job performance

Risk-taking (Rigtering et al., 2014)
RT1 - I value new strategies/plans even if I am not certain that they will always work
RT2 - To make effective changes to my offering, I am willing to accept at least a moderate level of risk of significant losses
RT3 - I like to take risks with new ideas

Proactiveness (Rigtering et al., 2014)
PA1 - I am constantly looking for new business opportunities
PA2 - My marketing efforts try to lead customers, rather than respond to them
PA3 - I work to find new business or markets to target

Innovativeness (Rigtering et al., 2014)
IN1 - I consider my business to be innovative
IN2 - My business is often the first on the market with new products and services
IN3 - Competitors in this market recognize me as a leader in innovation

ICTs Adoption (Beninger et al., 2016; Crittenden et al., 2019; Gichuki et al., 2018)
US1 - I use ICTs to present my products
US2 - I use ICTs to provide information to my current and potential customers about my products
US3 - I use ICTs to learn about ways to improve my sales
US4 - I use ICTs to make electronic payments related to my business

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THE INFLUENCE OF TECHNOLOGY LEADERSHIP ON UNIVERSITY LECTURERS INTEGRATING TECHNOLOGY IN THAILAND

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Abstract: *This research aimed to to examine the impact of technological leadership on the adoption and integration of technology by university lecturers in Thailand. The sample for this study comprised 317 university administrators and lecturers under the Ministry of Higher Education, Science, Research and Innovation who were divided into strata based on the size of their institutions. A questionnaire was used as a research instrument for data collection, while mean, standard deviation, and simple regression analysis were the statistical measures used in data analysis. Firstly, it was found that technology leadership of university administrators and the integration of technology by university professors were at a high level in all aspects. Secondly, technology leadership was found to have a .66 level of influence on the integration of technology by university professors, with all aspects showing a statistically significant correlation at the 0.05 level.*

Keywords: *technology leadership, technology integration, universities in Thailand, blended learning.*

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INTRODUCTION

The world has been changing rapidly in the 21st century as it is an era of globalization with accelerated progress in information technology. Faced with new challenging problems, humans have seen the infinite value of education and realized the need to adapt to lead a better life in the new century (Tissana Khammanee, 2018). The rapid transitions of the 21st century, or the Digital Age, have developed the dual nature of the human world. There is the traditional world with human-to-human interactions and the virtual world where communication takes place on social media. Such societal changes create a challenge for education management, leading to its transformations, for example, the creation of intelligent education systems. To keep up with the Digital Age, changes to educational processes; information technology plays a crucial role in these adjustments (Mat Rahimi Yusof et al., 2023). This is because technology can increase the efficiency of management and learning, leading to improvements in education management.

Technology is a significant catalyst that has led to several educational reforms. After the promulgation of the National Education Standards B.E. 2561 - the National Strategy for Teaching and Learning, a follow-up evaluation showed that Thai children did not have adequate "3R8C" or skills desirable in the 21st century. It was also found that management teaching was inconsistent with the standards and did not focus on children's performance. This underscored a significant issue with the curriculum and teachers, showing the need for adjustment in both teaching and attitudes. The latter must be more performance-driven to make an actual starting point for a successful educational reform (Asghar et al., 2022). In addition to considering students' individual goals and serving as a learning partner to guide and inspire them, teachers in the Digital Age must be able to integrate technology into their learning management strategies effectively. It is done so that students can reach their full potential and teachers can respond more effectively to the individual differences of their students. This is because technology makes learning more accessible, allowing students to learn more quickly and broadly (Sukanya Chamchoy, 2018). Recognizing the importance of using media and information technology in education management to help improve student quality, the Ministry of Education has since mandated an information technology and education master plan. The primary goal is to train people to use information and communication technology creatively while maintaining good governance and morality. There is also a focus on providing knowledge and competency in the development and application of information technology to teachers and other educational personnel (Areerachakul, 2015). It was found that educational institutions lacked solid information systems and did not provide adequate training to ensure that administrators had basic knowledge or understanding regarding using information and communications technology in education management and services. This highlights the importance of appropriate information and communications systems and administrative personnel development for educational institutions to understand the importance of information and communications technology in education management and service. As some teachers are still unprepared to integrate technology into the classroom, it is critical to encourage teachers to expand their knowledge and skills in developing innovative lessons and learning media using information and communication technology. Furthermore, there is a lack of support from high-level administrators in pushing for the integration of technology in educational institutions. This could lead to failure before it even starts, as the trust of high-level administrators is a critical starting point for the successful integration of information technology in educational institutions (Nguyen et al., 2023).

As a result, technology leadership has become an essential skill in today's world, especially with the accelerated growth of technology and its closer proximity to educational personnel in various departments ranging from teaching to support personnel. This change impacts administrators' leadership since they are obliged to understand these new conditions better. This is consistent with (Hu et al., 2023). that new-generation leaders must understand the significance of both current and future technologies. As a result, modern leaders must be able to use technology to maximize the development of humans and other resources. This is consistent with the Center for Advanced Study of Technology Leadership Development Technology Leadership in Education (CASTLE), which created a technology leadership framework. Technology leadership is essential for education administrators as it encourages stakeholders to participate in vision development for the broader use of technology. It motivates the use of technology in learning and the acquisition of appropriate technological knowledge to raise the level of education following curriculum standards and attain the highest levels of student achievement (Staniulienė & Lavickaitė, 2022). Technology has the potential to improve education significantly, and education administrators must be aware of its benefits. Teachers must prioritize and maintain a positive attitude toward technology and its educational applications to use it effectively. Educators must believe integrating technology into their classroom learning and instruction will benefit their students.

Given the issues raised above and the need for technological change in the Digital Age, education administrators must focus more on technology leadership. As a result, the researcher was intrigued by the levels of influence of technology leadership on technology integration by university lecturers in Thailand and their attitudes toward technology application in universities. The research instrument used in this study was explicitly developed following CASTLE's conceptual framework for technology leadership. The findings of this study could be used to develop technology leadership in education administrators to improve learning development, technology integration, and university educators' attitudes toward using technology in 21st-century learning development.

The author is now intrigued by the extent of influence that technology leadership has on the application of technology in teaching and learning, as well as on the attitudes of stakeholders associated with higher education institutions towards using technology. This curiosity forms the basis of the research objectives, which is to examine the impact of technological leadership on the adoption and integration of technology by university lecturers in Thailand.

Technology leadership and its effects on the integration of technology in educational institutions

In the literature review "technology leadership" in educational institutions is defined as the ability of educational administrators to use technology for effective management and vision creation, as well as to promote and support the use of technology in the integration of student-centered education (Huang et al., 2022). Technology leaders must be able to manage with a focus on universality and learn technology continuously to improve themselves and others and effectively achieve their goals. Furthermore, they must keep up with changes in the Digital Age world in the following areas: (1) leadership and vision, (2) teaching and learning, (3) productivity and professional skills, (4) support, administration, and operations, (5) measurement and evaluation, and (6) social, legal, and ethical issues. As a consequence, these aspects are used as the conceptual framework for this study and are explained below.

(2.1) "Leadership and vision" refers to the administration that motivates all parties to share a common vision in integrating technology to promote learning and create an environment conducive to vision awareness. (2.2) "Teaching and learning" (Alshareef & Tunio, 2022). refers to the administration that can elevate teaching and learning to meet curriculum standards and facilitate learning with a variety of technologies. This includes the ability to explain the characteristics of teaching and learning and to use technology that meets the needs of learners. (2.3) "Productivity and professional skills" refers to the administration that focuses on using technology in daily routine by ensuring continuous practice and building teams and learning groups in the organization to use technology in improving work and increasing productivity. It includes creating professional development opportunities for those who use or act as role models in technology integration (Bunjak & Černe, 2022). "Support, administration, and operations" refers to the administration that supports, promotes, and stimulates the demand for academic productivity resulting from the use of technology. They must also ensure the sustainability of such demand by encouraging teachers to use technology in the classroom or persuading unwilling or reluctant teachers to use information technology. (2.5) "Measurement and evaluation" refers to the administration capable of using technology for data collection, interpretation, and analysis, as well as for measuring and evaluating student learning outcomes. They should also be able to use technology to effectively and objectively analyze and evaluate an institution's administrative system. (2.6) "Social, legal, and ethical issues" refers to the administration with knowledge of social, legal, and ethical concerns. This includes ensuring that students use technology responsibly and safely and having adequate knowledge of intellectual property and copyright law.

According to a shared theme in Laufer et al., (2021). Leadership Perspectives on EdTech in a COVID-19 Reality— A Divider or Bridge Builder? this report elaborates how educational administrators are increasingly embracing internet-based studies to expand access, study and alliance. In response to the COVID-19 pandemic, the education system suddenly had to tilt towards online teaching. In response to this rapid shift toward digital technologies, 85 leaders from higher education institutions in 24 countries worked to overcome the digital divide. They focused on closing access gaps by increasing budgets for comprehensive online teaching across an entire system including not only the expense of electronic publishing and Web development, but also setting policy directions to hasten and guide the continual rapid transformation of digital technology.

Küçük, (2023). investigated of how technological instruction affects higher education, with particular attention given not only to its positive aspects but also its negative side. The study found that technology has become a major part of the modern world and exerted a great influence on higher education. This called for more thought, research, and experiment. The findings showed that the implementation of technology greatly affects the processes both of teaching and learning for faculty. It was found that if ICT is introduced into education then all three parties will benefit greatly, while at the same time either the permanence or stretching out over time for what has been acknowledged is guaranteed.

In a paper entitled "Transformational leadership and digital skills in HEIs During the COVID-19 Pandemic," research by Antonopoulou et al., (2021). revealed after 1-2 years, the entire world battled invasive COVID-19 pandemic, which affected so many different aspects of life. The study shows how leaders in educational change have adopted technology. It highlights that the whole process of learning and teaching, including testing media for effectiveness, is inextricably linked with the efficiency of teachers and learners both. Moreover, having a vision for teaching media equipment and support enhances teacher, student, staff and parent satisfaction among all stakeholders. This finding underscores the increasing need to integrate more digital technology into educational settings.

It is consistent with the findings of Nguyen et al., (2023). who investigated the characteristics of electronic leadership and the factors influencing the effectiveness of electronic leadership among elementary school administrators. The study discovered that integrating information technology into the curriculum, teaching, and learning, as well as teacher professional development, had a statistically significant impact on the effectiveness of electronic leadership for administrators at the .05 and .01 levels. The support of the school's board members and community was found to have a statistically significant influence on the school administrators' electronic leadership effectiveness at the .05 level. This is consistent with Mihardjo et al., (2019). findings on the level of technology leadership influencing the administration of basic education school administrators in Thailand's south. The study discovered that factors in professional development in technology, visions in technology, technology integration, and technology skills all significantly influenced educational administration, either directly or indirectly. This is consistent with the findings of Soni et al., (2023). who explored the effects of school administrators' technology leadership on the school environment. The study also examined the use of teachers' technology integration in indicating the effectiveness of teachers in top secondary schools under the Office of the Basic Education Commission at the sub-district level. It found that the technology leadership of administrators in top secondary schools at the sub-district level had a direct influence on teacher effectiveness, while the school environment had an indirect effect on teacher effectiveness through technology knowledge and integration. This study's model corresponded to the theoretical framework and could be used to explain 83% of teacher effectiveness. Islam et al., (2022). investigated the relationship between technology leadership and academic administration of school administrators under the Office of Non-formal Education and Informal Education in Saraburi Province, Thailand, in another study. The findings revealed that school administrators' technology leadership was highly correlated with their academic administration, with statistical significance at the .01 level.

Concepts and theories about the integration of technology use among educational personnel

According to the literature review, "technology integration by educational personnel" refers to the process of teaching and learning in which educators choose appropriate educational media and technology. Numerous media types for teaching and learning are available today, necessitating teachers' considerable skills in integrating technology into promoting and developing knowledge. It also requires teachers to be able to transform content into methods, processes, or practices used in learning activities, such as the use of educational technology, computers, multimedia media, the Internet, etc. (Duncan et al., 2022). The integration of technology by academic personnel could be divided into the following aspects

1. Integration with content knowledge refers to the ability to integrate technology into the content of subjects such as Thai language, Mathematics, Science, Social Studies, Religion and Culture, Health and Physical Education, Arts, Career and Technology, and foreign languages. This includes integrating perspectives, theories, concepts, evidence, and various theory tests, implementing them in practice, and further developing that body of knowledge. To accomplish this, teachers must have a good understanding of the subject's content to explain complex topics in an easy-to-understand manner and have the knowledge needed to study advanced content on their own (Lok et al., 2022).

2. Integration with pedagogical knowledge refers to integrating technology into the curriculum and the teaching and learning process. This includes the ability to conduct teaching and learning to achieve educational objectives. The focus of this integration is on student learning, lesson planning, class management, lesson plan development, putting the lesson plan into practice, assessment of student learning, and techniques, methods, or strategies for transferring in-class knowledge from teachers to enable learners to learn.

3. Integration with technological knowledge refers to the ability to integrate technology into work operations using technological knowledge of various approaches and solutions required in solving technology-related technical problems. This requires being up-to-date with new or valuable technologies, as well as possible applications of technology as a modern teaching and learning tool.

4. Integration with technological pedagogical content knowledge refers to integrating technology with lesson content and teaching methods using technological knowledge. This translates to using technology to design teaching per the nature of the subject while also ensuring an environment conducive to student learning. It includes choosing in-class technology to enhance the lesson, teaching approach, and student learning. It requires the appropriate use of technology to integrate with teaching methods and lesson content to facilitate learning management according to learning objectives (Tlemsani, 2022).

According to Ali, W. (2020). and his study 'Online and Remote Learning in Higher Education Institutes: A Necessity in Light of the COVID-19 Pandemic,' has not forgotten that amidst the spread of COVID-19, numerous higher education institutions worldwide have had to close down their campuses for long periods, seriously affecting student learning. Consequently, educational administrators not only have to make technology part of the teaching process, they must in doing so also foster flexibility and adaptability for students. The trend of universities moving towards online learning or E-Learning is clear from this study too. They also find that it plays a critical role for motivation in using technology better for learning, suggesting that teachers and staff at universities should utilize technology and technological devices to improve people's learning experiences. The study argues that the ability for online and distance learning is essential. and not only during lockdowns and times of social distancing compelled by the COVID-19 pandemic, but also in preparing for any future scenarios.

This is consistent with (Rybnikova et al., 2022). assertion that teachers' technology integration consists of three components: (1) teachers' computer proficiency, (2) teachers' belief, and (3) teachers' readiness. According to Koehler and Mishra, (2009). teachers' technology integration is based on the TPCK framework, later renamed TPACK, to communicate what teachers need to know to integrate technology efficiently. (1) Content

Knowledge (CK), (2) Pedagogical Knowledge (PK), (3) Technological Knowledge (TK), (4) Pedagogical Content Knowledge (PCK), (5) Technological Content Knowledge (TCK), (6) Technological Pedagogical Knowledge (TPK), and (7) Technological Pedagogical Content Knowledge (TPACK).

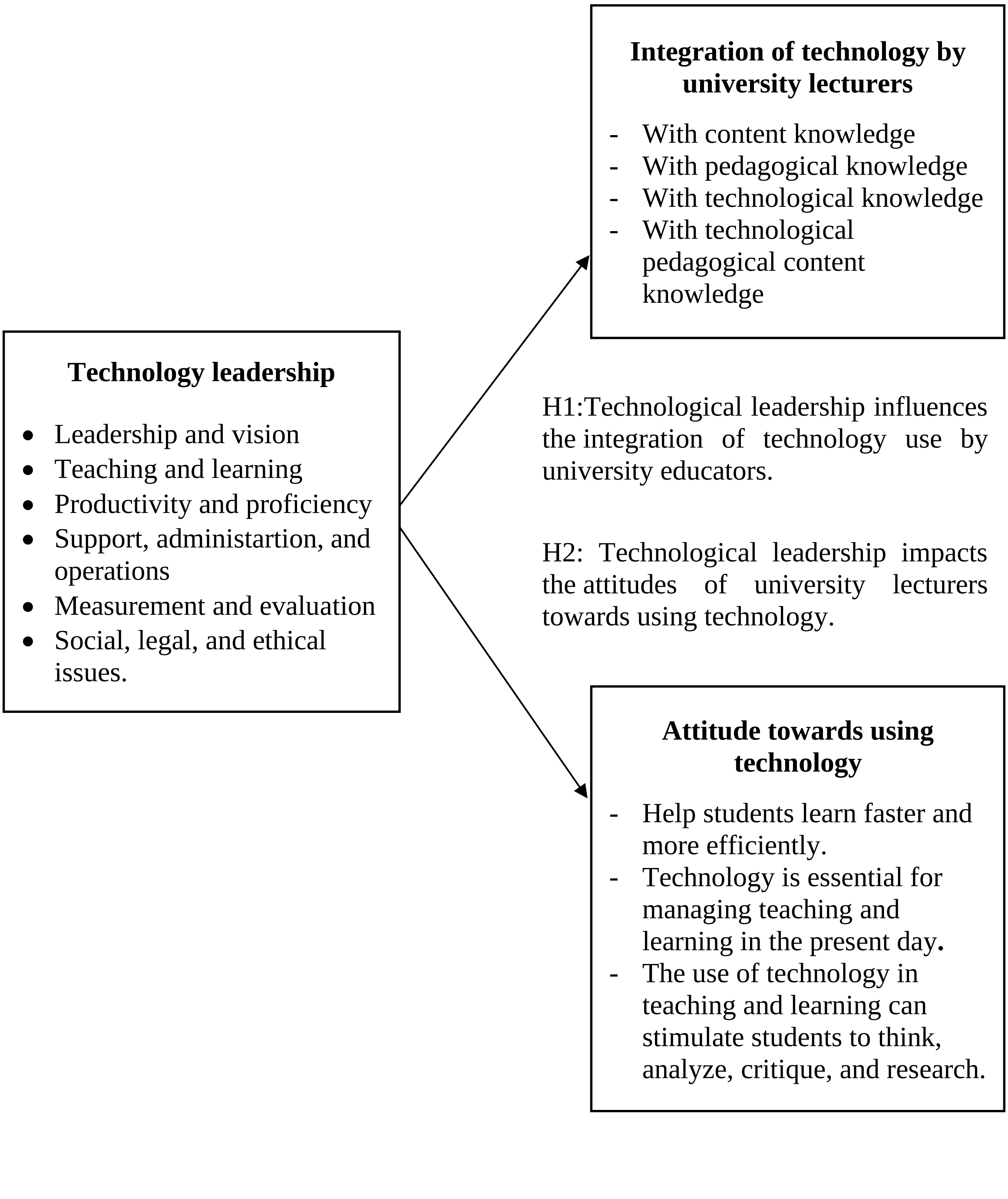
Chwen-Li, (2022). stated that the technology integration of teachers consists of 7 factors: (1) age, (2) teaching experience, (3) computer proficiency, (4) computer readiness, (5) teachers' beliefs, (6) teacher readiness, and (7) support. Inan and Lowther, (2010) stated that teacher technology integration involves 5 factors: (1) years of teaching, (2) technical support, (3) teachers' beliefs, (4) teachers' readiness, and (5) computer proficiency. (Ibrahim et al., 2022); stated that teachers' integration of technology consists of 4 components: (1) computing technology, (2) data-based technology, (3) telecommunication technology, and (4) educational technology. Mittal et al. (2022). stated that teachers' technology integration involves 3 components which are their (1) belief in technology, (2) support for technology usage, and (3) technology readiness. This is consistent with Amoako et al, (2022). who stated that teachers' integration technology consists of 3 components. (1) Computing technology includes generated commands or a set of "programs" that are created to complete tasks, such as information preparation, calculation, and online businesses. (2) Data-based technology is a source of data stored in digital codes developed parallel to computer technology. This is because computer technology is of little use without information or programs that can be stored and retrieved quickly in sufficient quantities to meet users' needs. Lastly, (3) telecommunication technology or technology for communications plays a role in linking various information through operating systems to provide more convenience.

The author is now intrigued by the extent of influence that technology leadership has on the application of technology in teaching and learning, as well as on the attitudes of stakeholders associated with higher education institutions towards using technology. This curiosity forms the basis of the research objectives, which is to examine the impact of technological leadership on the adoption and integration of technology by university lecturers in Thailand. The research hypotheses include: H1. Technological leadership influences the integration of technology use by university lecturers, and H2. Technological leadership impacts the attitudes of university lecturers towards using technology.

RESEARCH METHODOLOGY

This research conducted using a quantitative research methods, as follows: Quantitative: Survey: Use a structured questionnaire to quantitatively measure the level of technology leadership among university administrators and the level of technology integration by university professors. The questionnaire was designed to capture various aspects of technology leadership and integration. Sampling: The sample for this study would include 317 university administrators and lecturers under the Ministry of Higher Education, Science, Research and Innovation in Thailand. The sample was stratified based on the size of their institutions to ensure representation across different types of universities. Data Analysis: Analyze the collected data using descriptive statistics (Mean, Standard Deviation) to understand the overall trends and patterns in technology leadership and integration. Use Simple Regression Analysis to explore the influence of technology leadership on the integration of technology by university professors. This can help quantify the relationship and determine the extent to which technology leadership impacts technology integration.

Conceptual framework



Population and samples

1. The population used in this research was 1,718 lecturers from 135 universities under the Ministry of Higher Education, Science, Research, and Innovation,
2. The samples included were 317 university lecturers under the Ministry of Higher Education, Science, Research, and Innovation. The sample size was determined using the sample comparison table of Krejcie and Morgan (1970, p. 608). The samples were chosen with the Stratified Random Sampling method according to the university's size. The Simple Random Sampling method was then used by drawing lots to acquire a designated number of samples in each sample group, as shown in Table 1.

Table 1. Population and sample used in research [Source: own compilation]

University size	Number of universities	Total population (person)	Sample (person)
Small (1-120 people)	79	724	120
Medium (121-600 people)	52	706	163
Large (601-1500 people)	2	61	24
Extra large (1501 people or more)	2	227	10
Total	135	1,718	317

The sample for this study included 317 university administrators and teachers under the Ministry of Higher Education, Science, Research and Innovation, stratified based on the size of their respective educational institutions. This approach renders the sample a robust representation of the broader population for several reasons:

1. Stratification by institution size ensures a variety of viewpoints from both large and small universities, accurately reflecting the diverse environments in which technology is implemented.
2. The substantial number of participants, totaling 317, allows for the collection of comprehensive data, thereby minimizing the potential for bias that might arise from a smaller, less varied sample.
3. Given that the sample encompasses individuals from a wide range of institutions, categorized by their size, the findings are more likely to be generalizable and applicable to a broader population.

Research instrument

Relevant documents, concepts, theories, and research on technology leadership and its impact on technology integration by university lecturers were investigated. They were synthesized to determine terminologies and create a Rating Scale questionnaire using concepts, theories, and other data. The questionnaire was developed to cover all aspects of the research framework (Huang et al., 2022). before being given to five experts to assess its Content Validity, Index of Item Objective Congruence (IOC), content coverage, and linguistic clarity. The IOC index results were between 0.80 - 1.00 from expert opinions. The questionnaire was then adjusted until it was complete and appropriate before being used in a tryout survey with 30 non-sample respondents who shared similar characteristics as the sample group. The results of this tryout were used to calculate the reliability of the questionnaire using Cronbach's alpha coefficient formula yielding an overall reliability of.99.

Constructs the Indicators

The indicators and scales chosen for the study are based on various aspects of technology leadership and integration. These include factors like leadership and vision, teaching and learning, productivity and professional skills, and others. Each aspect is measured using an interval scale with responses ranging from 'Strongly Agree' to 'Strongly Disagree'. The justification for choosing these indicators and scales lies in their ability to comprehensively assess the complex dynamics of technology leadership and its influence on educational practices in the context of Thai universities. The study employs a structured approach to quantify and understand the relationship between technology leadership and technology integration, providing valuable insights for educational administrators and policy-makers. The indicators for this research constructed as follows:

Table 2. The indicators and scales chosen for the study are based on various aspects of technology leadership and integration. [Source: own compilation]

Construct the indicators	Methods of Measuring Variables	Level of Measurement	Sources of Information for the Researcher's Question Development
Technology leadership (X) - Leadership and vision - Teaching and learning - Productivity and professional skills - Support, administration, and operations - Measurement and evaluation - Social, legal, and ethical Issues	5 = Strongly Agree 4 = Agree 3 = Neutral 2 = Disagree 1 = Strongly Disagree	Interval Scale	(Huang et al., 2022) (Alshareef and Tunio, 2022); (Bunjak and Černe, 2022); (Nguyen et al., 2023); (Mihardjo et al., 2019);
Integration of technology by university lecturers (Y1) - With content knowledge - With pedagogical knowledge - With technological knowledge - With technological pedagogical content knowledge	5 = Strongly Agree 4 = Agree 3 = Neutral 2 = Disagree 1 = Strongly Disagree	Interval Scale	(Duncan et al., 2022); (Lok et al., 2022); (Tlemsani, 2022); (Rybnikova et al., 2022); (Chwen-Li, 2022)
Attitude towards using technology (Y2) - Help students learn faster and more efficiently. - Technology is essential for managing teaching and learning in the present day. - The use of technology in teaching and learning can stimulate students to think, analyze, critique, and research.	5 = Strongly Agree 4 = Agree 3 = Neutral 2 = Disagree 1 = Strongly Disagree	Interval Scale	(Ibrahim et al., 2022); (Mittal et al., 2022); (Amoako et al., 2022);

Data collection

Researcher has designated the period of data collection for this research as 1 January 2022 to 30 June 2022. This deliberate choice in timing is designed not to clash with any important university events-we aim for maximum participation and minimum distraction. To achieve this, the date has been chosen at a time when universities are not again gathered for end of semester exams or major meetings involving university administrators. Before the data collection process, systems and channels used for access to the online questionnaire were prepared to ensure ease of use for the respondents, who were university lecturers under the Ministry of Higher Education, Science, Research, and Innovation. This preparation process included setting the result display to automatically show the statistics of the answered questionnaire. The online questionnaire dashboard was regularly monitored to follow up on responses to obtain complete information from the designated number of respondents. The data collected from the completed questionnaires were processed and analyzed. All 317 sets of the questionnaire were answered, representing 100% response from the sample population.

Data analysis

The collected data were analyzed according to the research objectives. The technology leadership and technology integration parts of the questionnaire were analyzed using descriptive statistics such as Mean and Standard Deviation. Simple Regression Coefficient Analysis was used to examine whether technology leadership influenced the integration of technology by university lecturers in Thailand. The analysis was used to check if there would be correlations per the primary condition of Multiple Linear Regression.

RESULTS

The results on the level of technology leadership were analyzed overall and by aspect using Mean and Standard Deviation.

Table 4. Means and Standard Deviations of the level of technology leadership of university administrators under the Ministry of Higher Education, Science, Research, and Innovation, Thailand. [Source: own compilation]

Aspect	Technology Leadership of Administrators	$\bar{x}$	SD	level
1	Leadership and vision	4.22	.60	High
2	Teaching and learning	4.27	.58	High
3	Productivity and professional skills	4.23	.64	High
4	Support, administration, and operations	4.23	.59	High
5	Measurement and evaluation	4.22	.60	High
6	Social, legal, and ethical Issues	4.27	.59	High
	Overall	4.24	.55	High

From Table 4 Thailand's university administrators were found to have an overall high level of technology leadership with a Mean score of 4.24 and a Standard Deviation of .55. When considered by aspects, the administrators were found with a high level of leadership in all aspects, with leadership in "Teaching and Learning" and "Social, Legal, and Ethical Issues" being the highest rated aspects at the highest Mean score of 4.27, and Standard Deviations of .58 and .59 respectively. These were followed by leadership in "Productivity and Professional Skills" and "Support, Administrations, and Operations," which share a Mean score of 4.23, with Standard Deviations of .64 and .59, respectively. The leadership aspects found with the lowest Mean score were "Leadership and Vision" and "Measurement and Evaluation," with a shared Mean score of 4.22 and a shared Standard Deviation of .60.

Table 5. Means and Standard Deviations of the level of technology integration of university administrators under the Ministry of Higher Education, Science, Research, and Innovation, Thailand. [Source: own compilation]

Aspects	Technology Integration	$\bar{x}$	SD	level
1	Content knowledge	4.18	.60	High
2	Pedagogical knowledge	4.25	.57	High
3	Technological knowledge	4.21	.60	High
4	Technological pedagogical content knowledge	4.19	.62	High
	Overall	4.20	.54	High

From Table 5 Thailand's university lecturers were found to have an overall high level of technology integration with a Mean score of 4.20 and a Standard Deviation of .54. When considered by aspects, the lecturers were found with a high level of technology integration in all aspects, with the integration of technology with "pedagogical knowledge" being the highest rated aspect at the highest Mean score of 4.25, and a Standard Deviation of .57. This was followed by integration with "content knowledge"(Mean=4.22 and S.D.=60), "technological knowledge" (Mean=4.21 and S.D.=60), and "technological pedagogical content knowledge" (Mean=4.19 and S.D.=62), respectively.

Table 6. Mean and standard deviation of the attitude level towards technology usage among university professors. [Source: own compilation]

Aspects	Technology Integration	$\bar{x}$	SD	level
1	Help students learn faster and more efficiently.	4.24	.67	High
2	Technology is essential for managing teaching and learning in the present day.	4.37	.57	High
3	The use of technology in teaching and learning can stimulate students to think, analyze, critique, and research.	4.18	.73	High
	Overall	4.27	.54	High

From Table 6 Mean and standard deviation of the attitude level towards technology usage among university professors. Thailand's university lecturers were found to have an overall high level of attitude towards using technology with a Mean score of 4.27 and a Standard Deviation of .54. When considered by aspects, the lecturers were found with a high level of attitude level towards technology in all aspects, with " help students learn faster and more efficiently." being the highest rated aspect at the highest Mean score of 4.24, and a Standard Deviation of .67. This was followed by attitude towards using technology with " technology is essential for managing teaching and learning in the present day."(Mean=4.37 and S.D.=57), " The use of technology in teaching and learning can stimulate students to think, analyze, critique, and research." (Mean=4.18 and S.D.=73), respectively.

Table 7. The simple correlation coefficient between the technology leadership of university administrators and the integration of technology and attitudes towards the use of technology by professors in universities in Thailand. [Source: own compilation]

Technology Integration	$\bar{x}$	SD	level
Technology leadership of University Administrators (X)	1	.66*	.62*
Technology integration by university lecturers (Y_1)		1	.75*
Attitude towards using technology (Y_2)			1

Remark * With statistical significance at the 0.05 level.

From Table 7, it is found that the correlation coefficient between the technology leadership of university administrators (X) and the integration of technology (Y1) and attitudes towards the use of technology (Y2) by university professors is between .62 and .75. When considering the technology leadership of university administrators with the integration of technology and attitudes towards the use of technology by university professors in each aspect, the results are as follows:

The technology leadership of university administrators (X) has a statistically significant relationship with the integration of technology (Y1) at the .05 level, with a correlation coefficient (r) of .66.

The technology leadership of university administrators (X) has a statistically significant relationship with attitudes towards the use of technology (Y2) at the .05 level, with a correlation coefficient (r) of .62."

The integration of technology (Y1) has a statistically significant relationship with attitudes towards the use of technology (Y2) among university professors at the .05 level, with a correlation coefficient (r) of .75. This is in line with the initial agreement of data analysis by Multivariate Multiple Regression Analysis (MMR).

The results of the analysis of the technology leadership of university administrators that predicts the integration of technology and attitudes towards the use of technology by university professors, using the Multiple Regression Analysis - Enter Method, are as follows.

Table 8. Results of Standardized Regression Coefficient Analysis of technology leadership influencing technology integration by university lecturers in Thailand. [Source: own compilation]

Technology Integration	a	b	β	SE_b	t	p
Technology leadership (X)	1.45	.65	.66	.04	15.70*	.00

Remark * With statistical significance at the 0.05 level.

Technology leadership of university administrators was found to affect the integration of technology by university professors with statistical significance at the .05 level. The results were used to create a prediction equation as follows:

Prediction equation (standardized score) Y1 = .66(ZX)

Prediction equation (raw score) Y1 = 1.45 + .65(X)

Table 9. Results of Standardized Regression Coefficient Analysis of technology leadership influencing technology integration by university lecturers in Thailand. [Source: own compilation]

Technology Integration	a	b	β	SE_b	t	p
Technology leadership (X)	1.82	.58	.62	.04	13.84*	.00

Remark * With statistical significance at the 0.05 level.

From Table 9, it is found that the technology leadership of university administrators significantly affects the attitudes towards the use of technology by university professors at the .05 level. The researcher has constructed the following predictive equations:

Prediction equation (standardized score):
Y2 = .62 (ZX)

Prediction equation (raw score):
Y2 = 1.82 + .58(X)"

CONCLUSION

The results revealed Thailand's university administrators to have an overall high level of technology leadership. When considered by aspects, the administrators were also found with a high level of leadership in all aspects, with leadership in "Teaching and Learning" being the highest-rated aspect. This implies that the administrators supported their lecturers in integrating technology into their teaching, data analysis, and student performance assessment. The university administrators could encourage instructors to use evaluation data to improve teaching plans and learning management, as well as support the application of appropriate technology and innovation in teaching and learning management. This includes the administrators being able to promote professional development in terms of technology usage for lecturers and university personnel. The second highest-rated aspect was technology leadership in "Social, Legal, and Ethical Issues," which could imply that university administrators encouraged lecturers to have equal access to technology in universities. They could be a good example of using technology with caution and social responsibility under Thailand's Information Act. This includes the university administrators supporting and promoting mandatory safety, health, and environmental measures for technology usage in educational institutions. The administrators also formulated policies to raise awareness of the relationship between technology and social, legal, and ethical issues among lecturers and other academic personnel. This is consistent with an explanation of "technology leadership" (Alshareef & Tunio, 2022). as the ability of educational administrators to use technology for effective management and vision creation, as well as to promote and support the use of technology in the integration of student-centered education. Technology leaders must be able to manage with a focus on universality and learn technology continuously to improve themselves and others, effectively achieve their goals, and keep up with changes in the Digital world. The qualities of technology leadership lie in (1) leadership and vision, (2) teaching and learning, (3) productivity and professional skills, (4) support, administration, and operations, (5) measurement and evaluation, and (6) social, legal, and ethical issues.

Technology leadership was found to influence the integration of technology by university lecturers in Thailand at a statistical significance level of .05 and a standardized regression coefficient of 0.66. This is consistent with Duncan et al. (2022). who explored the effects of school administrators' technology leadership on the school environment and the use of teachers' technology integration in indicating the effectiveness of teachers in top secondary schools under the Office of the Basic Education Commission at the sub-district level. It found that the technology leadership of administrators in top secondary schools at the sub-district level had a direct influence on teacher effectiveness, while the school environment had an indirect effect on teacher effectiveness through technology knowledge and integration. This study's model corresponded to the theoretical framework and could be used to explain 83% of teacher effectiveness. Lok et al., (2022). investigated the relationship between technology leadership and academic administration of school administrators under the Office of Non-formal Education and Informal Education in Saraburi Province, Thailand, in another study. The findings revealed that school administrators' technology leadership was highly correlated with their academic administration, with statistical significance at the .01 level. This corresponds to Tlemsani, (2022). who explained that capable administrators could elevate teaching and learning to meet curriculum standards and facilitate learning using various technologies. This includes the ability to explain the characteristics of teaching and learning and to use technology that meets the needs of learners (Rybnikova et al., 2022).

SUGGESTIONS

Since technology leadership was found with a significant influence on the integration of technology by university lecturers in Thailand, it is critical to support and encourage technology leadership among education administrators. The administrators should also promote and support the use of technology in teaching and learning that improves learner quality. There should be continuous supervision and an environment conducive to teaching and learning management. Furthermore, the administration should prioritize technology management, particularly in developing teachers' knowledge and skills through training to promote technological operational and problem-solving skills. There should also be clear guidelines for teacher development.

CONTRIBUTION

The contributions of this research can be outlined as follows:

Enhanced Understanding: This research will deepen the understanding of the level of technology leadership among university administrators and its influence on the integration of technology by university professors in Thailand. This is a critical area of study given the increasing importance of technology in higher education. Empirical Evidence: The research will provide empirical evidence on the relationship between technology leadership and technology integration in universities. This can inform future research and theory development in this area.

Informing Practice: The findings can inform practice by providing insights that university administrators can use to enhance their technology leadership and promote more effective technology integration. Policy Recommendations: The research can also inform policy by providing evidence-based recommendations for the Ministry of Higher Education, Science, Research and Innovation in Thailand on how to support and enhance technology leadership and integration in universities. Methodological Contribution: The use of both qualitative and quantitative methods in this research can provide a more comprehensive understanding of the research problem. This mixed-methods approach can serve as a model for future research in this area. Contribution to Literature: This research will add to the existing body of literature on technology leadership and technology integration in higher education, particularly in the context of Thailand. This can be a valuable resource for other researchers studying similar issues in other contexts.

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