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Usage Intention of ChatGPT for Health in Turkey: An Extended Technology Acceptance Model

Metin Argan[a], Bülent Gürbüz[b], Mehmet Tahir Dursun[c], Halime Dinç[d], and Mehpare Tokay Argan[e]

[a]Faculty of Sports Sciences, Department of Sports Management, Eskişehir Technical University, Eskişehir, Turkey; [b]Faculty of Sport Sciences, Ankara University, Ankara, Turkey; [c]Denizli Vocational School of Social Sciences, Pamukkale University, Denizli, Turkey; [d]Faculty of Sports Sciences, Department of Recreation, Afyon Kocatepe University, Afyon, Turkey; [e]Faculty of Applied Sciences, Bilecik Seyh Edebali University, Bilecik, Turkey

ABSTRACT
The use of ChatGPT is spreading rapidly in the world. Although studies on the use of ChatGPT in healthcare are widespread, there have been very few studies examining ChatGPT technology in the context of the extended technology acceptance model (TAM), particularly from the perspective of end users. This study aims to investigate users' perspectives on utilizing ChatGPT in acquiring health information, employing the extended TAM that encompasses social influence, trust, and perceived surprise factors. The data were collected from a total of 1135 ChatGPT users in Turkey, a developing country, using convenience sampling. Confirmatory factor analyses and structural equation modeling were applied. Findings revealed that the variables affected each other within both TAM and extended TAM models. While focusing on health consumers' experiences with the use of ChatGPT is referred as the novelty of the study, it provides new insights into the use of ChatGPT in health-based research from the user's perspective.

KEYWORDS
ChatGPT; technology acceptance model; health; ease of use; usefulness; trust; Turkey

1. Introduction

ChatGPT has attracted increasing interest as researchers from a variety of backgrounds explore its potential usefulness, extending well beyond the discipline of computer science (Javaid et al., 2023). ChatGPT usage will likely increase in the future, with potential improvements to its capabilities. (Mijwil et al., 2023; AI, 2023). While it is rapidly attracting worldwide attention, especially nowadays, there is a lively debate about its advantages and potential harmful effects. (Salvagno et al., 2023). ChatGPT has caught the interest of researchers in almost every discipline, as an intelligent conversational agent capable of providing information and potentially offering a more user-friendly and interactive experience. Given its advantages over traditional chatbots, ChatGPT is regarded as the world's fastest growing application, with 100 million users within two months of launch, and is reported to have overtaken social media platforms such as Instagram and TikTok in terms of adoption rates (Menon & Shilpa, 2023).

Artificial intelligence technologies have revealed content such as commenting, sharing comments, evaluation, and adaptive text learning in the context of human-like interaction throughout user-friendly chatbots as ChatGPT (Chow et al., 2023). Even, the integration of conversational AI into established healthcare systems introduces a spectrum of challenges, with technical hurdles at the forefront, its potential for use in artificial intelligence-supported healthcare can be increased by improving precision and accuracy, personalization and context awareness, multidisciplinary research, user training, and engagement (Chow et al., 2024).

ChatGPT has various potential uses in healthcare, including improving patient experiences, assisting medical personnel in optimizing healthcare procedures, contributing to patient education, supporting medical care providers in developing patient-specific treatment programs, as well as offering a better healthcare solution to aid patient communication (Javaid et al., 2023). In a systematic review study, health-related ChatGPT was taxonomically divided into two main categories: application-oriented and user-oriented, and the user-oriented category includes the use of technology by patients and/or their relatives (Li et al., 2024). Chatbots used to answer users' questions and perform other tasks are the most effective use of ChatGPT. It has been emphasized that ChatGPT can produce human-like text in healthcare for better treatment and patient awareness of the disease (Javaid et al., 2023). Revealing the influencing factors for both the use of ChatGPT in healthcare and the acceptance of this technology from the perspective of users (patients or patient relatives), as well as determining the relationships between these factors, may contribute to the technology's user-centered perspective. There are versions of ChatGPT with various functionality (Lechien et al., 2024). Version 3.5 is available to everyone for free, however version 4.0 requires payment. Studies indicate that version 4.0 produces better outcomes than version 3.5 (Lin et al., 2023), despite the fact

CONTACT Mehmet Tahir Dursun mtdursun@pau.edu.tr Denizli Vocational School of Social Sciences, Pamukkale University, Denizli, Turkey

that some identify inaccuracies between the two versions such as changing answers over time and tending to provide erroneous responses (Frosolini et al., 2023; Morath et al., 2024).

TAM has been recognized as an important model for revealing the factors affecting the intention to use various technological innovations. Studies on TAM regarding ChatGPT have especially been focused on various contexts, including education (Saif et al., 2024), and adoption and usage (Tiwari et al., 2024). Rospigliosi (2023) called for further research in exploring ChatGPT and artificial intelligence. ChatGPT is becoming increasingly popular, both in developed and developing countries (George & George, 2023; Kshetri, 2023). The application of the health-based TAM in developing countries has been limited, and research in this regard complementary and comparative to that conducted in developed countries (Wu et al., 2008). The study of Hoque et al. (2017) demonstrates that, when assessing patients' and their families' attitudes in health services in developing countries, people's trust factors, usefulness, and ease of use are crucial components of internet-based health processes toward technology acceptance model. Given the sensitivity of the subject, further research is needed on the extent of ChatGPT usage among users in developing countries in the health context. Studies on the application of ChatGPT in healthcare generally focus on clinical and research perspectives (Nguyen & Pepping, 2023), ethical considerations (Wang et al., 2023), and health service as an innovative perspective (Javaid et al., 2023). However, the number of studies employing the extended TAM, which particularly looks for health information from the user's perspective and investigates ChatGPT technology within the context of the TAM, is rather limited. TAM, integrated by researchers with technological advancements, offers a more flexible way of explaining the underlying reasons for the acceptance and intention to use technology. It offers adaptability in its application in fields such as healthcare, allowing for the incorporation of new factors (Briones de Araluze & Cassinello Plaza, 2023). This statement highlights a notable gap in the literature. To address this gap, this study examines the use of the extended technology acceptance model, which includes social influence, trust and perceived surprise aspects, in acquiring health information from users' perspectives using ChatGPT.

The findings of this study have the potential to contribute in terms of theoretical and practical implications. First of all, theoretically, this study expands its boundaries by contributing to the existing literature on the use of ChatGPT in healthcare in Turkey. Second, TAM focusing on the use of ChatGPT in the healthcare domain has a pioneering nature and can provide theoretical contributions for the design of subsequent studies. This study also extends theoretical approaches to TAM and ChatGPT regarding users' use of ChatGPT in health information research by integrating new factors (social influence, trust and perceived surprise) into the existing TAM. The outcomes of this study are expected to greatly contribute to healthcare experts, managers, and professionals' understanding of the factors or mechanisms that drive users' adoption of ChatGPT. The study outcomes will allow managers and practitioners to indirectly compare the results in a developing country with those in developed countries. The findings of this study could be important when developing policies regarding the probable advantages and disadvantages of consumers accessing health information through such technology.

2. Theoretical framework and research hypotheses

2.1. ChatGPT and healthcare

Developments in artificial intelligence systems are revolutionizing the way we receive and access health-related information (Park et al., 2020). ChatGPT, a variation of OpenAI's generative pre-training transformer (GPT) large language models (LLMs), is the field's most successful public product (Wang et al., 2023). Among its range of LLMs, ChatGPT has achieved global recognition for its use of a transformer-based model, which enables efficient parallel processing of large amounts of data, leading to impressive capabilities in understanding and rendering natural language (Zhang et al., 2022). Furthermore, ChatGPT distinguishes itself by allowing free access to individual users as well as a user-friendly interface, thereby shifting the major user base of LLMs to the public, benefiting the greater community (Ofosu-Ampong et al., 2023). The widespread adoption of ChatGPT is a testament to the immense potential of LLMs. Artificial intelligence, inspired by the functioning of the human nervous system, seeks to imitate human intelligence in understanding, learning, and research (Wu et al., 2023). Artificial intelligence possesses advanced capabilities similar to those of humans, such as learning, problem-solving, recognizing situations, and communicating in natural language (Kocoń et al., 2023). Previous research has examined textual attributes, such as sentence length, in relation to chatbots (Uludag, 2024). ChatGPT additionally stands out for having the capacity to continue the conversation with follow-up questions. This feature provides the ability to ensure chat integrity and individualize responses by delivering customized answers to users' specific issues (Cai et al., 2023).

ChatGPT has the advantage of responding to user preferences and providing individualized responses, which traditional search engines are working to perfect (Gude, 2023). As an information provider, ChatGPT's acceptance or approval of these technologies by health-related users can greatly affect the adoption and effectiveness of these tools by individuals. Its deep learning algorithm system may provide human-like responses to user questions, making it a potentially helpful tool in various applications (Ofosu-Ampong et al., 2023). Albayati (2024) proposed that ChatGPT can be useful for medical diagnosis, treatment recommendations, patient education, and answering questions regarding medical procedures. In terms of the study's contribution, the fact that ChatGPT is still in the development stage adds to the body of knowledge in this field by using the technology acceptance model to understand the acceptance of AI chatbots and potential emerging technologies in the field of health, as well as the roles of the determining factors.

Furthermore, AI-powered technology can support chatbots, which are useful in the healthcare industry and enable patients, healthcare providers, and patients' families to access and acquire more comprehensive information (Siddique & Chow, 2021).

2.2. Extended technology acceptance model (TAM)

One of the widely accepted approaches to assessing technology use by users is TAM (Tao et al., 2020). TAM was first used by Davis (1985) and was later conceptualized to explain how consumers perceive and adopt new technologies (Davis, 1989). Adapted from theories in the social-psychological/behavioural literature (Theory of Planned Behaviour, Ajzen, 1991), TAM states that the behavioural antecedent in actual technology use is intention (Davis, 1989). Behavioural intention is influenced by individuals' attitudes, which are determined by two basic constructs: perceived ease of use and perceived usefulness (Davis, 1989). The theory posits that an individual's behavioural intentions and actions toward adopting a new technology are mostly influenced by their perceptions of its usefulness and simplicity of use (Sabah, 2016). Perceived usefulness is an individual's assessment of how using a particular system will improve their experience (Davis & Venkatesh, 1996). It is also noted that perceived usefulness has a direct effect on behavioural intention and perceived ease of use has a direct effect on perceived usefulness (Davis, 1989). Another important factor to consider is perceived ease of use, which refers to users' perceptions of the degree of complexity in using a particular technology (Davis & Venkatesh, 1996). It has to do with people's perceptions of how straightforward and easy it is to pick up new technological skills (Davis, 1989). Individuals are more likely to adopt new technologies if they perceive that they will be able to learn how to use them quickly and easily (Del Giudice et al., 2023). TAM, which is designed to examine people's psychological systems toward new technology, is commonly used to investigate human-robot and/or human-AI interactions (Duong et al., 2023).

It has been proposed that TAM-based models should be updated to better reflect the educational context (Al-Azawei & Alowayr, 2020; Hoi, 2020). Furthermore, Sepasgozar (2022) stated that the two essential premises of TAM, perceived utility, and perceived ease of use, should be measured by specific constructs in the educational context. As a result, in several contemporary educational studies, the terms effort expectancy and performance expectancy have been replaced with perceived usefulness and perceived ease of use. They are used to describe student technology adoption, such as the usage of mobile devices for language learning (Hoi, 2020), mobile learning (Al-Azawei & Alowayr, 2020) and mobile internet use (Nikolopoulou et al., 2021).

New variables have been added to studies aimed at developing the TAM, which is commonly used to assess the acceptability of technology. For instance, in the study of Briones de Araluze and Cassinello Plaza (2023), the TAM was expanded and the social influence variable from the UTUAT model was included. In another study, the model was expanded to include the influence of perceived usefulness on trust (Albayati, 2024; Choudhury & Shamszare, 2023). Based on this approach, we focused on the adoption of ChatGPT in users' health information research by including three variables, social influence, trust, and perceived surprise, in addition to the TAM. Social influence (SINF) is a vital social force influencing adoption decisions (Venkatesh et al., 2003). The theory of reasoned action (TRA) (Fishbein & Ajzen, 1977) and TAM2 (Venkatesh & Davis, 2000) include the subjective norm as the antecedent of the concept and present SINF as a distinct factor in the voluntary adoption of new technologies (Venkatesh et al., 2003). The sustained and broader adoption of new technology is intimately tied to positive reactions from potential users, emphasizing the importance of their engagement with technology as a primary source of concern (Abbas Naqvi et al., 2020). Social influence is defined as the extent to which individuals' intention to use a new system or technology is influenced by significant others (Hoi, 2020). Social influence also refers to an individual's perception that significant others, such as friends, family members, or peers, believe they should use a particular form of technology (Menon & Shilpa, 2023).

Positive social impact can increase user perception of ChatGPT's usefulness and ease of use, reduce perceived risks and barriers to adoption and increase user confidence in their ability to use the technology effectively. Negative social impact, on the other hand, can cause uncertainty and concern about the reliability, accuracy and ethics of ChatGPT, strengthening user resistance to change (Menon & Shilpa, 2023). In the early stages of technology diffusion, when the innovation is completely new to users and they are unsure how to use it, social impact is critical (Adapa et al., 2018). In the case of the adoption of new technologies, individuals often experience uncertainty and turn to their immediate networks for guidance (Mu & Lee, 2017). Mohammadi (2015) stated that social impact is the strongest predictor of students' desire to adopt mobile learning.

Trust is the basis of the human-computer relationship and is considered the psychological motivation of behaviour (Tiwari et al., 2024). Trust has been acknowledged as a crucial factor in technology adoption (Dirsehan & Can, 2020; Lin et al., 2020; Muflih, 2023), and users' willingness to interact with a system is determined by their confidence in the security of their data (McKnight, 2005). Users are more likely to adopt technology when they perceive that their information is secure, and the benefits outweigh the risks (Jo, 2023). Trust, which was previously defined and added to the model in the use of the TAM, especially in online shopping, is defined in the context of ChatGPT as users' willingness to take risks based on the recommendations offered by this technology (Turja et al., 2020). This definition is underpinned by users' belief that the technology can execute a particular task correctly, keeping in mind the possibility of negative consequences. If chatbots can accurately interpret consumers' needs, and if AI technology continues to advance, people may come to trust these technologies (Laudon & Traver, 2017). A study examining patients' and clinicians' perceptions of chatbots, especially in the field of healthcare, revealed a relationship between users' trust in AI-based healthcare chatbot services and their intentions to use them (Van Bussel et al., 2022). Chatbot technology is believed to possesses the necessary characteristics to perform healthcare services as expected (Mcknight et al., 2011). The element of trust is an important antecedent that affects the adoption behaviour of health technologies (Fogel & Nehmad, 2009).

Surprise, considered a basic emotion (Ekman & Friesen, 2003), is the state felt when a stimulus does not conform to expectations (Izard, 2013; Meyer et al., 1991). Surprise is a result of the difference between an individual's expectations and perceptions (Hutter & Hoffmann, 2011). ChatGPT's hardware, capabilities such as user interaction, question and chat maintenance and personalized responses to each user are growing daily expectations. The perceived surprise in this study is due to the results arising from ChatGPT's limited, unlimited response capability and the lack of direction in human-ChatGPT interactions. People have their own experiences and ways of perceiving ChatGPT, with different questions and answers they receive when using ChatGPT. Therefore, an expectation of surprise when encountering new technologies may play an essential role in their use and adoption. When considering an innovative technology, the first dimension represents the fact that the technology itself is impressive and exceeds expectations, which means that it is treated as a surprise. Second, the outcomes obtained using this technology have been deemed unexpected or surprising by its users.

2.3. Proposed model and hypothesis development

2.3.1. Social influence, perceived usefulness, and perceived ease of use

Previous research has supported the notion that there is a connection between social influence and individuals' perceptions and actions (Tiwari et al., 2024). According to TAM, *perceived usefulness* and *perceived ease of use* are influenced by external factors, such as the demographic characteristics of the user and social influences (Albayati, 2024). Social influence is characterized as a subjective norm and represents people's behaviour being influenced by their environment (Venkatesh et al., 2003). Indeed, the theory of acceptance and use of technology (Menon & Shilpa, 2023; Venkatesh et al., 2003) and the theory of planned behaviour (TPB; Fishbein & Ajzen, 1977) recognize subjective norm as a significant/notable aspect in directing behaviour. In studies based on UTUAT and TBP in technological product usage behaviour, the subjective norm reflecting social impact was applied (Ajzen, 1991; Venkatesh et al., 2003). Social influence measures the impact of the social environment, which includes colleagues, peers, parents, and educators (Hoi, 2020). The influence of the environment and psychological pressure can affect people's intention and behaviour toward using a technological product. When using new technology, individuals tend to feel uncertainty and rely directly on their social networks for guidance (Mu & Lee, 2017). People engage in such behaviours to conform to group standards or to boost their public image (Bearden et al., 1989). Tornatzky and Klein (1982) found that adoption depends significantly on whether an innovative technology is compatible with the standards of potential adopters. The beliefs of technology users are largely shaped by the social environment (Mohammadi, 2015) and how easy and useful it is for students to use mobile devices in language learning is related to their beliefs formed by their surroundings (Hoi, 2020). Previous studies have indicated that ease of use and perceived usefulness, which affect intention, are affected by a person's social environment (Albayati, 2024). In fact, one of these studies revealed that subjective norms played a leading role in the benefits of e-portfolio acceptability and the ease of use of this technology or program (Abdullah et al., 2016). In this study, we estimate that the social context will influence ChatGPT's functionality in health research as well as the ease of use of this technology's user-friendly interface. The hypotheses developed based on the above literature and discussions are presented below.

H_1. Social influence positively affects the perceived usefulness of ChatGPT for health.

H_2. Social influence positively affects the perceived ease of use of ChatGPT for health.

2.3.2. Perceived usefulness, trust, and perceived surprise

User trust in ChatGPT impacts developing positive attitudes and increasing the intention to use the technology (Heerink et al., 2010). As a result of perceived usefulness, it is predicted that trust in the technology and its outcomes will improve. Laumer et al. (2019) determined that trust is essential in shaping people's use of chatbots for disease diagnosis. Similarly, Choudhury and Shamszare (2023) study results underlined that the phenomenon of trust has a decisive importance in the adoption of ChatGPT. The intention to use ChatGPT is primarily based on the quality of the information in health-related searches and how useful it will be for the person. As a result, it is acceptable to conclude that perceived utility plays a primary role in the emergence of trust.

It can be argued that there is a relationship between perceived surprise (Hutter & Hoffmann, 2011), which refers to the difference between expectations and perceptions, and perceived usefulness. A growing number of studies have investigated the effect of surprise on consumer satisfaction (Vanhamme, 2000), customer satisfaction (Heilman et al., 2002; Vanhamme & Snelders, 2001), viral marketing (Lindgreen & Vanhamme, 2005) and purchasing decisions (Ozer et al., 2020). People who seek out ChatGPT regarding health may view this situation as positive if the technology itself and the results obtained appear to be beneficial (Tlili et al., 2023). Perceived usefulness can thus be an impressive factor in that the user's perception of the result is surprisingly worthwhile. In our study, we expect that perceived usefulness will arise from trust in ChatGPT and the surprisingly beneficial outcomes derived from these interactions. Thus, the following two hypotheses were developed.

H_3. Perceived usefulness positively affects the trust in ChatGPT results.

H_4. Perceived usefulness positively affects perceived surprise toward ChatGPT.

2.3.3. Perceived usefulness and perceived ease of use as influencers of attitude

Attitude toward technology use is affected by perceived usefulness and perceived ease of use, according to the TAM (Albayati, 2024; Davis, 1989; Tiwari et al., 2024; Venkatesh & Bala, 2008). Perceived usefulness refers to the extent to which the user believes that the technology will increase its performance or functionality (Bhattacherjee, 2000). Individuals are more inclined toward acceptance and adoption of new technology if they perceive that it will help them achieve their goals or objectives (Albayati, 2024). Perceived usefulness is assessed based on an individual's motivation to use the technology. Similarly, ease of use in TAM is a key factor that positively affects attitudes toward technological innovation (Tiwari et al., 2024; Venkatesh & Bala, 2008). Attitude may be a variable having the negative impact of perceiving technology as complex on the intention to use it. If a user perceives this technology as difficult or complex to learn or use, it may have a negative effect on technology acceptance (Albayati, 2024). Thus, there is an association between perceived usefulness and perceived ease of use, which are the core factors in TAM. It is mentioned that as the perceived ease of use of technology increases, there is a positive relationship between perceiving the technology as useful and this may have a positive effect on attitude. Therefore, it is hypothesized that:

H_5. Perceived ease of use positively impacts the perceived usefulness of ChatGPT.

H_6. Perceived usefulness positively impacts users' attitudes toward using ChatGPT.

H_7. Perceived ease of use positively impacts users' attitudes toward using ChatGPT.

2.3.4. Trust, perceived surprise, and attitude as influencers of behavioural intention

The attitudes and intentions of users toward technology can be influenced by their trust in it (Kim et al., 2023; Tiwari et al., 2024). Users who trust ChatGPT are more likely to be motivated to use the technology (Tiwari et al., 2024) and have favorable attitudes and intentions to use it (Heerink et al., 2010). Therefore, people's willingness to use ChatGPT could be based on their trust in the technology. In the study of Albayati (2024), trust in ChatGPT as a regular assistance tool was found to have a positive effect on behavioural intention. Furthermore, Nguyen et al. (2021) survey revealed that users' intentions to continue using chatbot services are primarily driven by their trust in the chatbot. A healthcare study conducted through interviews indicated that trust is critical in deciding whether individuals will use chatbots for disease diagnosis (Laumer et al., 2019). Trust in chatbots plays a crucial role in people's decision to use the technology. Choudhury and Shamszare (2023) recent research concluded that trust is crucial for users' adoption of ChatGPT. This finding supports the idea that trust positively affects the actual use of technology and highlights the critical role of trust in the adoption and implementation of new technological solutions. Thus, we propose the following research hypothesis:

H_8. Trust positively influences the user's intention behaviour toward using ChatGPT for health.

Perceived surprise is considered a factor that influences intention in the research model. Surprise, which results from the difference between the technology user's expectations and perceptions (Hutter & Hoffmann, 2011), can trigger the intention to use if it is positive. The performance expectancy of ChatGPT is represented by perceiving the information produced by ChatGPT as valuable and useful (Tlili et al., 2023) and may be related to the user's perceived surprise. The term perceived surprise refers to the fact that the health information received because of ChatGPT surprises the user positively or leaves them satisfied with the outcome. The usefulness of information is positively affected by factors such as timeliness, scope, reliability and quality of information, which in turn predict an individual's intention to use the information (Cheung, 2014). Therefore, it is reasonable to conclude that perceived surprise influences a stronger intention to use when the benefit from using ChatGPT is activated. In this study, we expect that the surprising perceived beneficial outcomes of ChatGPT in health research will affect the intention to use the technology. Based on this assumption, the following hypothesis is proposed.

H_9. Perceived surprise positively influences the user's intentional behaviour toward the use of ChatGPT for health.

Moreover, the positive impact of user's attitudes on behavioural intentions has been linked with the perceptions of ChatGPT. The relationship between attitudes toward technology and use intention is well-documented (e.g., Albayati, 2024; Davis, 1989; Tiwari et al., 2024; Venkatesh & Davis, 2000). Considering that the attitudes toward technological innovation shape behaviour action (Davis, 1989; Venkatesh & Bala, 2008), attitudes regarding ChatGPT will likely influence behavioural intentions as health information seeking. Many studies based on TAM have highlighted the relationship between attitude and intention. (Tiwari et al., 2024). Consistent with the theoretical and practical evidence offered above, as well as the ongoing discussions, a positive attitude toward ChatGPT is likely to motivate as a precursor to the intention to use technology to gather health information. Based on this, the final hypothesis in the model is as follows:

H_{10}. Attitudes toward ChatGPT positively influence the user's intention behaviour toward using ChatGPT for health.

The proposed model illustrating the integration between the TAM and the three external constructs is shown in Figure 1.

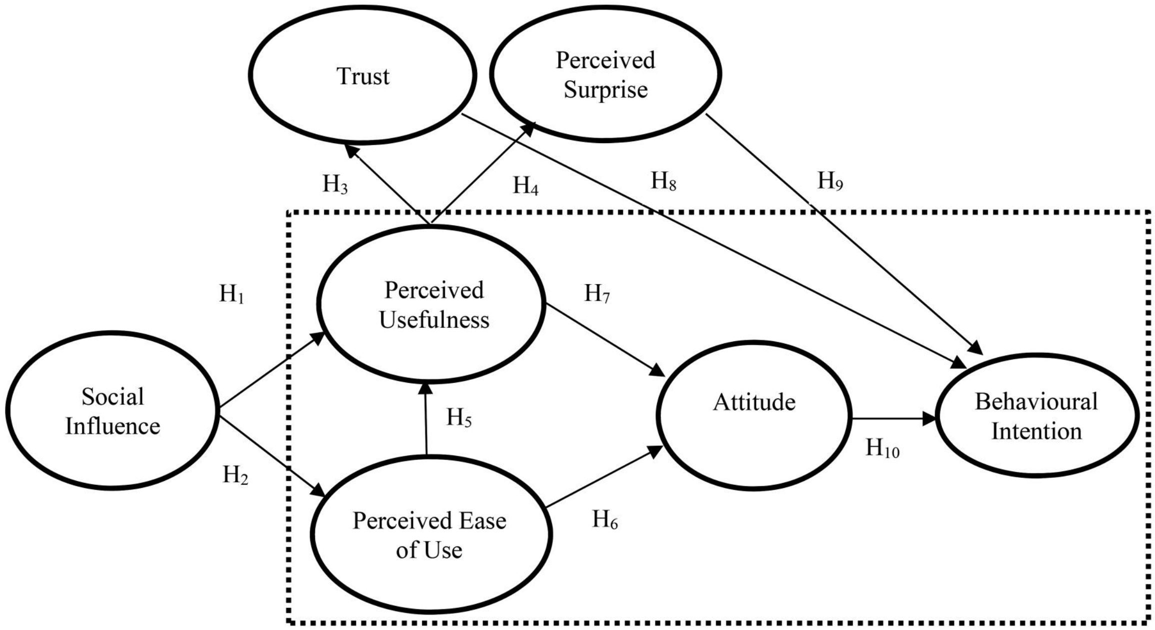

Figure 1. Proposed model.

3. Methodology

3.1. Sample and procedure

The research population consists of people using ChatGPT in healthcare services, and the research sample is 1135. Convenience sampling was used to gather data using survey technique using a questionnaire between August 15 and December 15, 2023. Additionally, the respondents were given the option to share that with their social environment by means of this notice "*Please share this questionnaire with your environment those who use ChatGPT for health.*" Questionnaire forms were sent to individuals receiving healthcare services and seeking health-related information. At the onset of the questionnaire, respondents were informed of the purpose of determining their current state of knowledge regarding ChatGPT. Surveys proclaiming not to use ChatGPT and having inaccurate or missing data were removed and not included in the analysis. As a result, data from 1135 ChatGPT users were used for analysis. The demographic data of the participants was presented, and analysis of the research data was carried out using the IBM SPSS program, whereas the structural model was tested using the AMOS program. Structural equation modelling based on partial least squares was used to examine the measurement and structural model.

3.2. Measures

According to the purpose of the research, quantitative techniques were preferred to examine the relationships between the use of ChatGPT on health and various variables, and the data collection process was carried out with a survey form containing statements about these variables. The questionnaire includes three items measuring social influence and three items measuring perceived ease of use related to ChatGPT use, which are taken from Beh et al. (2021); three items measuring perceived usefulness adopted from Lu et al. (2009); and three items measuring trust and attitude adopted from Abbas Naqvi et al. (2020). Additionally, the behavioural intention scale (3 items), which was taken from the study of Zeithaml et al. (1996), and the perceived surprise scale (3 items) were used from the research of Hutter and Hoffmann (2014). A 5-point Likert-type scale was used to rate each statement (1 being strongly disagreed and 5 being strongly agreed). The questionnaire also included questions regarding participants' demographic information, such as gender, marital status, age, and income level. The scales have been proven to have intercultural validity and reliability, and they are frequently used in the relevant field. First, the study's scales were translated into Turkish, and three academicians with extensive knowledge of the fields in which they work were consulted. The scales' translators were proficient in both Turkish and English. Additionally, a native English speaker who works as a researcher in the field approved the finalized scale items in English. After 118 participants participated in a pilot test, the reliability of the scales was found to be at the intended level; as a result, data collection was allowed to continue without any statements being removed from the survey form.

4. Results

In this study, 1135 users of ChatGPT were surveyed, and all the data gathered was analysed. Most respondents are individuals who use the internet for health-related research (983, 86.6%), singles (856, 75.4%), people in the 18–25 age group (635, 55.9%), and people whose average income is "15K-30K" (452, 39.8%), based on the demographic characteristics of the respondents that make up the research sample (Table 1). The largest sample group in this study, which focuses on persons discussing ChatGPT use, is the 18–25 age group, which is well-known for the tendency to use new trends such as artificial intelligence, technology, and the internet.

Table 1. Respondents' demographics.

		N	%
Age	18 to 25	635	55.9
	26 to 35	330	29.1
	36 to 45	113	10.0
	46 years and above	57	5.0
Gender	Female	549	48.4
	Male	586	51.6
Marital status	Single	856	75.4
	Married	259	22.8
	Non-observed	20	1.8
Education	Primary school	50	4.4
	Secondary school	266	23.4
	Undergraduate	758	66.8
	Postgraduate	61	5.4
Income	15 K and below	359	31.6
	15001 to 30 K lira	452	39.8
	30001 to 45 K lira	217	19.1
	45001 to 60 K lira	63	5.6
	60001 lira and above	44	3.9

4.1. Measurement model

Confirmatory factor analysis (CFA) was applied in order to confirm the model before testing hypothesis. In conclusion, the model was confirmed by the findings of the AMOS program. Thus, the model fit indices as the RMSEA (0.05), χ^2/df (4.43), CFI (0.98), TLI (0.97), NFI (0.97), GFI (0.94) and AGFI (0.91) are suitable (Byrne, 2001).

4.1.1. Reliability and convergent validity

The measurement model was examined in this study in order to verify the consistency of the statements and the discriminant and convergent validity of the scales. According to Table 2, all standardized factor loadings are above 0.50, as suggested by Bagozzi et al. (1991). Cronbach's alpha values were used to measure internal consistency. Cronbach's alpha ratings in the 0.89–0.94 range indicate an appropriate level of model reliability (Hair et al., 2017). The average explained variance (AVE) value was used to ensure convergent validity. The AVE values (0.82-0.90) of the structures in this study were found to be above the threshold values, which Fornell and Larcker (1981) states was set at 0.50.

4.1.2. Multicollinearity

Examining the variance inflation factor (VIF) value in the regression model provides a simple evaluation of multicollinearity (Thompson et al., 2017). Multicollinearity between independent variables is defined as threshold < 0.1 and VIF > 10 (Kyriazos & Poga, 2023). Table 3 indicates the values of all the independent variables (social influence, perceived of usefulness, perceived of ease of use, perceived surprise, trust and attitude) that fit these requirements.

4.1.3. Discriminant validity

Discriminant validity was provided by the Heterotrait-Monotrait (HTMT) ratio. One of the methods that has been extensively utilized in recent years for discriminant validity is the HTMT ratio, which is an emerging method

Table 2. Reliability and convergent validity.

Factors		Factor loading	Alpha	CR	AVE
Social influence (SINF)	SINF1	0.926	0.93	0.95	0.88
	SINF2	0.950			
	SINF3	0.939			
Perceived of usefulness (PUF)	PUF1	0.926	0.93	0.95	0.84
	PUF2	0.911			
	PUF3	0.937			
	PUF4	0.893			
Perceived of ease of use (PEU)	PEU1	0.919	0.89	0.93	0.82
	PEU2	0.898			
	PEU3	0.908			
Perceived surprise (PSR)	PSR1	0.920	0.91	0.94	0.85
	PSR2	0.934			
	PSR3	0.919			
Trust (TST)	TST1	0.927	0.93	0.95	0.88
	TST2	0.949			
	TST3	0.944			
Attitude (ATT)	ATT1	0.946	0.94	0.96	0.90
	ATT2	0.958			
	ATT3	0.949			
Behavioural intention (BI)	BI1	0.938	0.93	0.95	0.87
	BI2	0.947			
	BI3	0.926			

Table 3. Multicollinearity.

Factors	VIF
(Constant)	
Social influence (SINF)	2.64
Perceived of usefulness (PUF)	5.07
Perceived of ease of use (PEU)	2.31
Perceived surprise (PSR)	3.62
Trust (TST)	3.83
Attitude (ATT)	3.55

Table 4. Discriminant validity.

Factors	SINF	PUF	PEU	PSR	TST	ATT	BI
SINF	**0.938**	0.723	0.719	0.726	0.765	0.772	0.738
PUF	0.677**	**0.916**	0.767	0.900	0.850	0.831	0.834
PEU	0.657**	0.702**	**0.905**	0.724	0.740	0.697	0.713
PSR	0.671**	0.836**	0.655**	**0.921**	0.792	0.767	0.792
TST	0.714**	0.804**	0.677**	0.732**	**0.938**	0.843	0.793
ATT	0.725**	0.783**	0.642**	0.714**	0.793**	**0.948**	0.843
BI	0.688**	0.779**	0.651**	0.730**	0.739**	0.820**	**0.932**

Note: The values below the diagonal represent the correlations between the variables, and the diagonal numbers in bold indicate the square roots of the AVE. The values above the diagonal are the values of the heterotrait-monotrait ratio (HTMT).

(Henseler et al., 2015). According to the recommended standards, HTMT ratios should be less than 0.9 (Hair et al., 2017). Accordingly, as can be seen in Table 4, the analysis of the variables, it is confirmed that all values are the desired threshold values. Thus, the existence of relationships between the structures used in the data collection tool is revealed. The square roots of AVE must be greater than the correlation of the associated constructs in order for discriminant validity to be met. Table 4 illustrates that these values as shown as bold are acceptable high (Hulland, 1999).

4.1.4. Structural model and hypothesis testing

After testing the hypothesis, the structure of the study indicates that the model fit indices are suitable and show the

RMSEA (0.06), χ^2/df (5.36), CFI (0.97), TLI (0.96), NFI (0.97), GFI (0.92) and AGFI (0.90). As a result, all values of the current study fit the suggested thresholds and standards (Byrne, 2001). According to AMOS suggestion, four modification indices were applied to model shown in the Figure 2.

Figure 2 and Table 5 demonstrate the measurement model's outcomes. As a result, each hypothesis was approved. Regression weights *(β)* were used to test and prove hypotheses 1 through 10, as shown in Table 5. According to H1, perceived usefulness is positively and significantly affected by social influence ($\beta = 0.32$, $p < 0.01$). With respect to H2, perceived ease of use was positively affected by social influence ($\beta = 0.57$, $p < 0.01$). Additionally, the H3 hypothesis's association between perceived usefulness and trust is supported ($\beta = 0.93$, $p < 0.01$). The H4 hypothesis states that people's perceived surprise is influenced by the perceived usefulness in accordance with their derive from using ChatGPT for health-related purposes ($\beta = 0.96$, $p < 0.01$). Moreover, with H5, it appears that ChatGPT 's perceived usefulness is positively impacted by its perceived ease of use ($\beta = 0.51$, $p < 0.01$). According to hypotheses H6 and H7, ChatGPT's perceived ease of use ($\beta = 0.14$, $p < 0.01$) and perceived usefulness ($\beta = 0.88$, $p < 0.01$) have an impact on individuals' attitudes. As indicated by H8 and H9, people's behavioural intentions are positively influenced by perceived surprise ($\beta = 0.09$, $p < 0.01$) and trust ($\beta = 0.28$, $p < 0.01$). Hypothesis H10 also confirms that attitude toward ChatGPT has an effect on behavioural intention ($\beta = 0.56$, $p < 0.01$).

5. Discussion

5.1. Key findings and theoretical implications

This study aimed to test the extended TAM, which includes social influence, trust, and perceived surprise factors, in obtaining health information through ChatGPT from the perspective of individuals from Turkey, an emerging country. To the best of our knowledge, this is the first study to use ChatGPT in health and integrate social influence, trust, and perceived surprise factors into the extended TAM. The results of this study validate the proposed extended TAM by applying CFA and SEM. This study found that the main factors in the TAM, as well as additional factors in the extended TAM, including social influence, trust, and

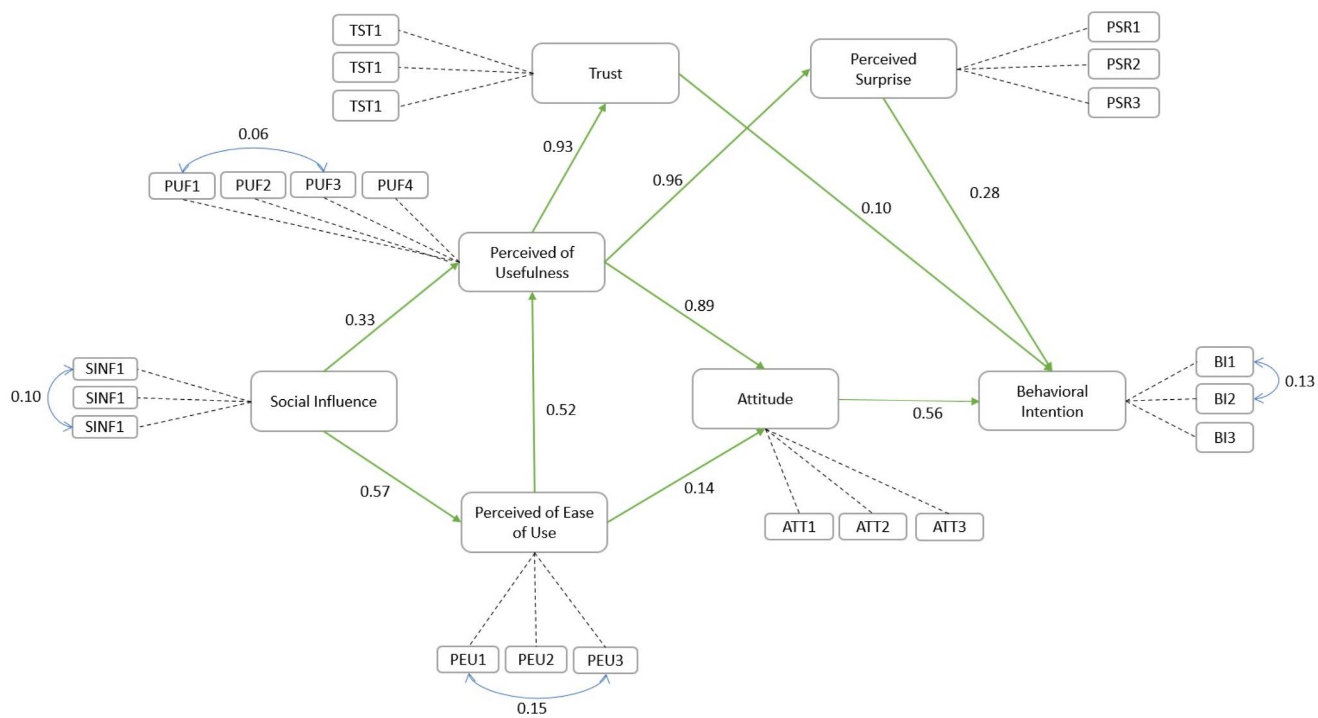

Figure 2. Structural model.

Table 5. Results of the testing hypothesis.

Hypothesis	β	S.E.	CR	p	Hypothesis testing
H1. Social influence → Perceived usefulness	0.32	0.027	12.21	0.00	Supported
H2. Social influence → Perceived Ease of Use	0.57	0.024	23.85	0.00	Supported
H3. Perceived usefulness → Trust	0.93	0.029	32.66	0.00	Supported
H4. Perceived usefulness → Perceived surprise	0.96	0.029	32.89	0.00	Supported
H5. Perceived Ease of Use → Perceived usefulness	0.51	0.037	13.99	0.00	Supported
H6. Perceived Ease of Use → Attitude	0.14	0.041	3.42	0.00	Supported
H7. Perceived usefulness → Attitude	0.88	0.043	20.54	0.00	Supported
H8. Trust → Behavioural intention	0.09	0.036	2.70	0.00	Supported
H9. Perceived surprise → Behavioural intention	0.28	0.038	7.39	0.00	Supported
H10. Attitude → Behavioural intention	0.56	0.032	17.39	0.00	Supported

perceived surprise, were effective in using the ChatGPT for health purposes. Social influences were hypothesized to be an antecedent to ease of use and perceived usefulness as major predictors of ChatGPT acceptance. The effect of social influence on both perceived usefulness and ease of use was significant, however, its effect on ease of use for ChatGPT was greater than that on perceived usefulness. A possible explanation for the high relationship between social influence and perceived ease of use may be that individuals learn to use this technology by being influenced by their social environment. This finding agrees with Ma and Huo (2023), who found that users' performance expectations of ChatGPT are affected by social influence.

In accordance with many previous studies (Hussein et al., 2022), the results of this study indicated that the perceived ease of use of the AI technology, ChatGPT also exhibited a strong positive influence on the perceived benefit of the technology used or to be used. The result of the current study indicates that perceived usefulness is a strong determinant of trust, perceived surprise, and attitudes toward using ChatGPT. This result is consistent with the individual's attempt to accept technology due to its perceived benefit. Consistent with Davis et al. (1992), we found that perceived usefulness influences user attitudes toward ChatGPT use more than perceived ease of use. A possible explanation for this could be that ChatGPT's interface is perceived as easy by individuals. Thus, the perceived benefit of technology allowed individuals to form more positive attitudes toward ChatGPT (Albayati, 2024; Bhattacherjee, 2000).

Intention to use ChatGPT is the dependent variable in this study and in almost all studies regarding TAM, which is considered an indicator of actual search transactions over ChatGPT. This study considers perceived surprise and trust as predominant factors influencing individuals' intention to use ChatGPT in the context of health. To the best of our knowledge, few studies have simultaneously examined the role of perceived surprise and trust in the intention to use ChatGPT. As expected, trust, perceived surprise and user attitudes toward using ChatGPT have a significant effect on triggering behavioural intention. It is not surprising to learn from the research results that individuals with a positive attitude towards ChatGPT might be willing to engage in participation behaviour. Thus, the influence of user attitudes toward using ChatGPT on behavioural intention was higher than the other two factors, trust and perceived surprise. This result agrees with many previous studies that supported the strong effect of attitudes on intention (Albayati, 2024; Tiwari et al., 2024; Venkatesh & Davis, 2000).

This study offers several theoretical contributions to the existing literature regarding TAM, ChatGPT, and health. First, it extends the application of TAM (Davis, 1989) to the context of health. In addition, while the extended TAM is used here within the general context of health, it also can yield insights into other related fields, for example, in the exploration of the experience of specific diseases (e.g., cancer or oncologic care) and other subjects (e.g., nutrition or diet). Second, the current study contributes to the extended TAM literature by combining variables from the "traditional" model of user acceptance (perceived usefulness, perceived ease of use and attitude) with variables specific to the ChatGPT for health purposes (social influence, trust and perceived surprise). By providing an improved theoretical understanding of ChatGPT user experience, our extended TAM may facilitate the acquisition of further knowledge to deepen our understanding of the factors influencing behaviour intention in the healthcare context. Third, the results of the study will also be beneficial in terms of enriching the literature related to the extended TAM by offering empirical evidence in emerging countries based on the use of ChatGPT in the field of health.

5.2. Practical and managerial implications

The results of this research provide practical implications for ChatGPT in developing countries, those who use this technology to obtain health information and healthcare providers. AI is an important area for health because of its important role in emerging countries. Revealing the levels and intentions of individuals in developing countries to use AI technology is an important contribution to its implementation. In this context, the findings of our study reveal the factors affecting the intention to use ChatGPT in Turkey, a developing country. Describing the situation of relevant AI technology in developing countries may have practical implications for strategies to be implemented in other developing countries. However, when using ChatGPT in healthcare, the limitations and challenges need to be carefully evaluated (Biswas, 2023). Regarding users of ChatGPT, we suggest that individuals who use AI technology, especially to obtain sensitive health-related information, should be cautious and confirm search results with accredited healthcare organizations or healthcare professionals. For this reason, it will be important to take precautions for users to benefit from ChatGPT technology on sensitive issues such as health. Over-reliance on AI technologies such as ChatGPT for health-related advice could potentially lead to misinformation and resulting health risks (Choudhury & Shamszare, 2023). Regarding risk reduction, we recommend that users confirm the health suggestions, they receive from ChatGPT, with a physician or healthcare professional before implementing them. Regarding healthcare providers, ChatGPT developers should also focus on warnings, especially in artificial intelligence software that makes recommendations on vital issues such as health. Efforts should focus on improving ChatGPT's ability to distinguish between queries it can handle securely and queries that should be routed to human experts (healthcare professionals) (Choudhury & Shamszare, 2023). Potential risks can be reduced by encouraging shared responsibility and collaboration among AI developers, experts, researchers of user behaviour, as indicated by Choudhury and Shamszare (2023). Therefore, the findings of this study have important implications for practitioners, health managers, individuals seeking health information via ChatGPT, physicians, and health professionals.

6. Limitations and future research

It is necessary to acknowledge that this study has some limitations that provide new avenues for future research. Although the sample of our study may be considered relatively large, it is limited in generalizability because of the non-probability nature of our sampling procedure and its application in a single developing country, Turkey. Therefore, future studies should be implemented in similar contexts or context representing developed countries to provide both more generalizable results and comparisons. Second, the demographic distribution of the sample group of the research may be considered as another limitation. There was an imbalance in the sample concerning the participants' age, education and health problems. Approximately three-quarters of the participants did not have health problems and had graduate or postgraduate degree. Additionally, the average age of the research participants (mean: 27.31 sd: 8.74) can be considered limiting regarding the use of ChatGPT on a sensitive issue such as health. However, it is acceptable that users who have adopted ChatGPT are mostly young (Gude, 2023) and educated people (Shahsavar & Choudhury, 2023), both in developed countries and especially in developing countries. However, we recommend studies that will focus on the use of ChatGPT in searching for information about a specific health condition in individuals over middle age. Third, in our proposed extended TAM, three factors that are assumed to directly or indirectly affect the intention to use ChatGPT in health are integrated. However, other restrictive and encouraging factors affecting the use of ChatGPT in health, which is an important and sensitive area, also need to be taken into account. Therefore, as highlighted by Biswas (2023), we recommend future studies investigate not only the factors (i.e., perceived value, perceived performance and novelty value) that positively affect the intention to use ChatGPT in health but also the factors (i.e., perceived severity and perceived vulnerability) that restrict it (Zhang et al., 2019). Moreover, we recommend the implementation of comprehensive models in ChatGPT that integrate theory of planned behaviour (TBP) and personal health differences models with TAM, as implemented in mobile health services by Zhang et al. (2019). Fourth, the current study focused on the ChatGPT experience in general, that is, without focusing on a specific health condition or disease. Further studies should consider exploring how the extended TAM applies to the different specific health contexts and what influencing and limiting factors may be integrated. Also, certain textual analysis methods as mentioned in the previous study (Uludag, 2024) can be adopted to assess level of technology acceptance.

7. Conclusion

The current study suggests the applicability of TAM in acquiring health information from AI technology, ChatGPT, with the inclusion of additional factors to model the adoption of ChatGPT in Turkey, an emerging country. The extended TAM was validated in the context of Turkey as an emerging country. This study attempted to test a conceptual model of three main factors and three influential factors considered in the literature to be antecedents to the intention to use ChatGPT for health information. TAM was used as a base in shaping the conceptual model, which is extended here to incorporate three additional constructs (social influence, trust, and perceived surprise) related to ChatGPT. All hypotheses in the proposed extended model were confirmed. The importance of the three antecedents to intention for ChatGPT in terms of their effects came in the following order: attitude, perceived surprise, and trust. Moreover, social influence as an antecedent variable proved to be important in predicting perceived usefulness and perceived ease of use for ChatGPT. Finally, perceived ease of use has a positive effect on perceived usefulness, and the perceived usefulness of ChatGPT exhibits a strong positive influence on both trust and perceived surprise. When comparing the effect of perceived usefulness on trust in ChatGPT's results and users' perceived surprise, the effect of perceived usefulness on perceived surprise was higher.

Disclosure statement

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ORCID

Metin Argan http://orcid.org/0000-0002-9570-0469
Bülent Gürbüz http://orcid.org/0000-0003-2424-2111
Mehmet Tahir Dursun http://orcid.org/0000-0003-3907-2469
Halime Dinç http://orcid.org/0000-0002-2391-5508
Mehpare Tokay Argan http://orcid.org/0000-0002-8996-082X

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About the authors

Metin Argan is a professor at the Department of Sport Management, Eskisehir Technical University in Eskisehir, Turkey. He earned his PhD in marketing at the Anadolu University. He has published about 100 research papers. His research interests include marketing, sponsorship, health marketing, and consumer behavior.

Bülent Gürbüz is a professor at the Faculty of Sport Sciences, Ankara University in Ankara, Turkey. He earned his PhD in Physical Education and Sports at the Institute of Health Sciences, Gazi University. He has published many research papers on marketing, recreation management, leadership, volunteering, and therapeutic recreation.

Mehmet Tahir Dursun is an associate professor at Pamukkale University in Denizli, Turkey. He has earned his PhD in tourism from Anadolu University, Turkey. His research focuses on travel, consumer behavior, and tourism.

Halime Dinç holds a PhD in sport management and recreation at Eskisehir Technical University in Turkey. She has five years of experience working in academic and research institutions. Her work has been published in well-reputed journals. Her research interests are in customer experience, recreation management, and leisure time.

Mehpare Tokay Argan is a professor at the faculty of applied sciences at Bilecik Seyh Edebali University. Her research interests include health marketing, tourism marketing, and consumer behavior. She holds a PhD in marketing from Anadolu University, Institute of Social Sciences.