HHAI 2024: Hybrid Human AI Systems for the Social Good
F. Lorig et al. (Eds.)

doi:10.3233/FAIA240200

Trust in AI Chatbots: The Perceived Expertise of ChatGPT in Subjective and Objective Tasks

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Abstract. With the advancement and increasing availability of AI based chatbots, it becomes relevant to better understand how people use and perceive these systems. Previous research shows that trust in algorithms varies as people assume algorithms are more capable of handling tasks of objective knowledge domains than of subjective ones. The present study investigates how perceived expertise, perceived risk, trust, and perceived usefulness vary in objective and subjective knowledge domains and how this translates in use intention. In an online study, 602 participants watched an interaction video with ChatGPT, showcasing either an objective task or a subjective task. The results demonstrate an indirect effect of knowledge domain on use intention via perceived expertise, perceived risk, trust, and perceived usefulness in serial. This demonstrates how various factors impact the use intention, and how important it is to consider the usage context.

Keywords. Chatbots, ChatGPT, AI, perceived expertise, perceived risk, trust, perceived usefulness, use intention, knowledge domain

1. Introduction

For a few years now, AI based systems have been assisting people not only with internet searches for fact-based information on certain topics but also in creative and imaginary fields of activity that were previously thought to be reserved for humans [1–4]. AI based chatbots like ChatGPT can be used in more objective contexts like teaching parts of the STEM syllabus [5], or more subjective and creative tasks such as the generation of stories and ideas [6]. While research delves into ChatGPT's capabilities, a gap exists in understanding user perception [7].

Given the recent and unfamiliar ability of generative AI to come up with new ideas and even own creative writing, it is important to investigate how this influences the way users perceive the AI based system and how this alters their trust in the system as well

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as their use intentions. First conclusions on these questions can be derived from earlier research on algorithms. People have greater aversions toward algorithms in subjective knowledge domains because they assume that algorithms are more proficient in handling objective tasks [8]. Specifically, perceived expertise has been demonstrated to be an important mediator that might lead to higher use intention for tasks of objective knowledge domains [9]. But also further constructs appear to be related to attributed expertise. Studies have indicated that people perceive a lack of ability for algorithms to perform subjective tasks specifically in high risk situations and that this is related to less trust [10]. Previous research findings have already identified trust as a main predictor regarding one's intention to use chatbots [11], which is significantly influenced by the perceived risk of relying on a technology in a certain situation [12]. Accordingly, people are more cautious of the usage as the likelihood of negative outcomes increases [12,13]. People will consider technology more useful and see greater benefits if they have trust in it [14,15], once again highlighting trust as a crucial factor for successful user interaction. Numerous studies have shown that usefulness predicts use intention (overview by Lee et al. [16]), including in the context of chatbots [15,17]. This is due to the fact that if technology provides value and makes it simpler to complete tasks, the likelihood of using it increases [18–20]. While research has therefore addressed singular relationships of several constructs related to differential use intention of algorithms, the state of the art lacks a test of a coherent model for understanding the use intention for new chatbots which pose novel opportunities for generating creative output.

Therefore, the present study investigates the perception of chatbots, proposing a mediation model in which objective and subjective knowledge domains lead to a different level of perceived expertise which influences perceived risk, trust, perceived usefulness, and intention to use in serial.

2. Theoretical background

2.1. Knowledge domain

Research has identified different attitudes toward AI, including algorithm aversion [21] and algorithm appreciation [22], where people either tend to rely on a human rather than an algorithm or vice versa. Here, the context, such as the knowledge domain, in which someone is using a certain technology plays an important role in their attitude toward it [23]. Mahmud et al. [8] found that task factors, like subjectivity or morality, are important for the emergence of algorithm aversion. Knowledge domains can be distinguished into objective knowledge domains, which contain tasks with measurable and quantifiable facts, and subjective knowledge domains, where tasks offer a wide scope for interpretation and are based on one's intuition or attitude [10,24].

Chatbots can potentially be used in different contexts, such as coding and medicine [25] or in the education sector, for answering questions for students and explaining the solution paths [5]. They can also be used in more creative knowledge domains, such as the generation of stories and content ideas [6]. The present study distinguishes between subjective and objective knowledge domains in which a chatbot can be used and investigates to what extent these two lead to different perceptions and use intentions toward the chatbot.

2.2. Use intention

One of the most important variables to quantify the impact the knowledge domain has on future usage is use intention. According to the theory of planned behavior [26], intention directly influences the shown behavior. In the technology acceptance model (TAM), it has been demonstrated that behavioral intention to use the technology is related to actual system use [27].

Previous research has already demonstrated that task factors, such as objectivity or complexity, serve as significant predictors of use (intention) [8]. The same is true for perceived expertise [28] as well as perceived risk [29], trust [11,15] and perceived usefulness [15,30]. With regard to task factors, Castelo et al. [10] showed that people rely less on algorithms when used in subjective domains compared to objective domains, indicating a task-dependent algorithm aversion. Similarly, other studies have shown that for subjective domains, human recommendations are preferred [31], while for objective domains, more reliance was placed on algorithms [22,24]. These results confirm the MABA-HABA framework ("Machines Are Better At vs. Humans Are Better At"; [32]), which states that in certain domains machines have benefits over humans, while human abilities are superior in others. This goes along with people thinking algorithms are not effective in subjective domains [10], as they are perceived as unable of feelings or emotions [33].

Consequently, we postulate that *the objective knowledge domain has a stronger effect on use intention than the subjective knowledge domain (H1).* This is further specified when we look at potentially mediating effects, as they affect the impact of the knowledge domain on use intention and are explained in more detail below.

2.3. Perceived expertise

One of these factors potentially influencing use intention is perceived expertise, which relates to the basic expectations users have toward systems when operating them and can be defined as the users' perception of the professional level of a technology when interacting with it [28]. Perceived expertise has been demonstrated to be an important mediator for the effect that knowledge domain has on the use intention since expertise is rather attributed to systems when handling objective tasks [9]. In this line, previous research findings showed that perceived expertise has an impact on use intention in the context of technology [28].

In addition, Gupta et al. [34] found perceived credibility, based on the dimensions of trustworthiness and expertise [35], significantly predicts behavioral intention to use technology. Therefore, users are expected to be more willing to use chatbots in a certain domain when perceived expertise is higher: *The effect of knowledge domain on use intention is mediated by perceived expertise (H2).*

Another potential mediator for the relation of knowledge domain and use intention is perceived risk. Perceived risk can be defined as "the user's perception of the possibility and importance of loss when using the system" [29]. A certain risk exists when using chatbots, as they can give false answers, generate nonsensical content, or portray misinformation [36]. Therefore, perceived risk is a relevant factor in the use intention.

2.4. Perceived risk

It has been shown that the perceived risk of an activity is highly domain-specific [37] and depends on the perception of the perceived expertise [10]. This phenomenon is expected to be found in objective and subjective knowledge domains. Trivedi [38] found that perceived risk mediates the effect of perceived quality regarding the system, information, and service on user experience, showing that perceived risk reduces the impact of the three quality dimensions on customer experience. Furthermore, perceived risk leads to lower user satisfaction which in turn negatively influences the use intention [39]. Similarly, Wu and Gao [29] showed that perceived risk was significantly negatively associated with use intention. Therefore, the following hypothesis is formulated: *The effect of knowledge domain on use intention is mediated by perceived risk (H3).*

2.5. Trust

The intention to use technology in a specific context is influenced by the trust in it, emphasizing the important role of trust in the usage of technology [11]. Trust can be defined as “the extent to which a person is confident in, and willing to act on the basis of, the words, actions, and decisions of another” [40]. To determine how trustworthy someone or something is, three characteristics are influential: ability (abilities, qualities, and skills to influence another in a given area), benevolence (the degree to which a trustee is thought to have good intentions), and integrity (trustee meets certain standards) [41].

The ability in a domain might vary greatly depending on the context, resulting in very high trust in one domain and low trust in another [42]. Hoff and Bashir [43] argue that task-specific factors influence one's level of trust in automated systems. In terms of AI, it has been shown that people trust and rely less on algorithms when they are used for subjective knowledge domains as opposed to objective knowledge domains [10]. People must decide if, how, and to what extent to trust algorithm-based technology whenever they come across it [44]. The given trust affects the intention to use and the actual use of technology like chatbots [11,45,46]. Thus, it is postulated that: *The effect of knowledge domain on use intention is mediated by trust (H4).*

2.6. Perceived usefulness

In the context of automated technology, Ghazizadeh et al. [47] added trust to the original TAM [27], showing that trust has a positive effect on perceived usefulness, which in turn influences use intention. According to the TAM, perceived usefulness is a determinant of behavioral intention to use technology, which in turn influences the actual use. Perceived usefulness is defined as “the degree to which a person believes that using a particular technology would be beneficial” [27]. The TAM has been supported by numerous studies (overview by Lee et al. [16]), including in the context of chatbots [15,17]. The likelihood that users will use technology increases significantly if it provides value to them and makes it simpler to complete a task [18–20].

As shown by Al-Emran et al. [48], several knowledge-related elements play a substantial role in determining perceived usefulness. They discovered a positive link between perceived usefulness and knowledge acquisition, defined as the application of prior information and the creation of new knowledge. According to Kim et al. [49], there is a difference between functional AI compared to social AI regarding perceived usefulness, highlighting the usage context as an influencing factor. This leads to the belief that the knowledge domain has an impact on perceived usefulness and that there is also a difference regarding perceived usefulness for objective and subjective domains: *The effect of knowledge domain on use intention is mediated by perceived usefulness (H5).*

2.7. Proposed research model

According to the previously demonstrated effects, a research model (Figure 1) is proposed, which postulates a linkage between these factors to explain how the use intention of chatbots varies in different knowledge domains. In a study, Castelo et al. [10] have already investigated whether the characteristics of a task influence the willingness to use algorithms and identified a task-dependent algorithm aversion. More specifically, people rely less on algorithms when used in subjective compared to objective knowledge domains [10]. Perceived expertise is a relevant factor in the formation of trust and trust is lower for subjective tasks [9,10], therefore, we assume that people attribute higher expertise to chatbots in objective than in subjective knowledge domains. Castelo et al. [10] showed that drawing on expertise that is mistakenly perceived as being of high quality seems to carry greater risks in some tasks than in others. Thus, we assume that lower perceived expertise may lead to higher perceived risk and that perceived risk also differs in different knowledge domains.

The perceived risk has an impact on trust in technology because as the likelihood of false information increases, individuals are more cautious of the usage [12,13]. The trust that users have in technology again positively influences its perceived usefulness [14,15]. This is also shown in the Automation Acceptance Model with the extension that perceived usefulness in turn influences use intention [47]. It is therefore assumed that *the effect of knowledge domain on use intention is mediated in serial by perceived expertise, perceived risk, trust, and perceived usefulness (H6).*

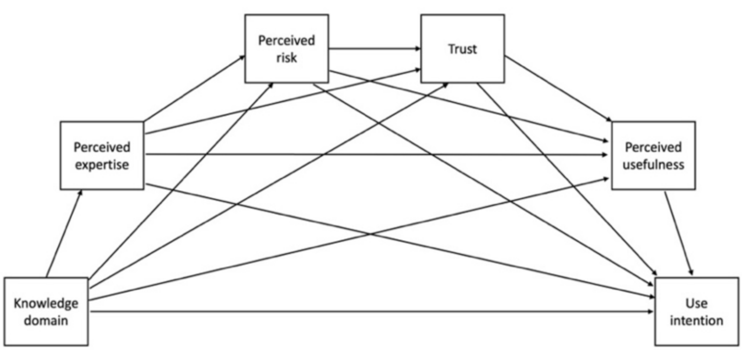

Figure 1. Conceptual diagram of the proposed research model.

3. Method

The present study was preregistered on Open Science Framework (OSF; https://doi.org/10.17605/OSF.IO/9HZJG). The design of the study was approved by the ethics committee of the University of Duisburg-Essen (ID 2305SPKT0269).

3.1. Study design

The present online experimental study involved a randomized between-subjects design with two conditions: objective knowledge domain, consisting of the stimuli giving directions [10] or solving a scientific school exercise, and subjective knowledge domain, consisting of the stimuli recommending a gift [10] or writing a poem [1,4]. In each stimulus participants saw a screen video of an interaction with ChatGPT May 24 Version in German language in which the following instructions were given to ChatGPT: giving directions – "*How do I get from the university in Duisburg to the university in Münster by car?*" (n = 146), solving a scientific school exercise "*Explain to me briefly the term prokaryotes*." (n = 150), recommending a gift – "*What can I give my mother for her birthday? Give me 3 suggestions.*" (n = 149) and writing a poem – "*Write a short poem on the theme of 'country life' in the style of Goethe*." (n = 149).

3.2. Procedure

The participants were recruited via the online panel Prolific and received a compensation of £2.25 for their participation. Prerequisites for participation were to speak fluent German, a minimum age of 18, participation via laptop or PC, and an approval rate of at least 98% at Prolific (https://www.prolific.com).

The participants first answered questions about their socio-demographics (gender, age, formal education) and experience with ChatGPT before being randomly assigned to one of four conditions, followed by the respective stimulus video. Afterward, perceived expertise, perceived risk, trust, perceived usefulness, and use intention were measured before a manipulation check was presented. In addition, attitude toward ChatGPT, affinity for technology, mistrust, and subjective domain knowledge were assessed but these variables were not part of the analysis.

3.3. Measurements

In the following, all questionnaires used in the study are presented. For the scales of perceived expertise, perceived risk, trust, perceived usefulness, and use intention, participants were told to refer to the knowledge domain shown in the video when answering the items.

The dependent variable use intention was measured using the intention to use questionnaire [50], with two items (e.g., "I plan to use ChatGPT often."). Answers were given on a 5-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*) (α = .880). Perceived expertise was assessed using the perceived expertise questionnaire [51], including five 5-point bipolar items (e.g., "expert" vs. "not an expert"). Participants indicated their impression of ChatGPT by selecting the appropriate level between the pairs of items (α = .887). The perceived risk to use technology questionnaire [52] was used to measure perceived risk. The scale contains seven items (e.g., "ChatGPT is not completely safe.") and is answered on a 5-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*) (α = .904). Furthermore, the trust questionnaire [52], including the subscales "integrity/process", "benevolence/purpose", and "ability/performance", was used to measure trust (e.g., "ChatGPT is honest."). It has 40 items, answered on a 5-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*) (α = .930). Perceived usefulness was measured using the perceived usefulness questionnaire [50], which contains three items (e.g., "Using ChatGPT will improve my work.") with a 5-point Likert-scale (1 = *strongly disagree*, 5 = *strongly agree*) (α = .924).

The experience with ChatGPT was measured using the following self-formulated item: "How often have you used ChatGPT before?". Participants were asked to choose one of four possible answers: "never", "once", "several times" and "often". To check the quality of the stimulus material, the perceived objectivity of the task seen in the video was measured as a control variable. Participants were asked to what extent they felt the task given to ChatGPT in the video was subjective or objective using a 6-point bipolar item (1 = *subjective*, 6 = *objective*).

3.4. Sample

According to the simulation-based calculations of Fritz and MacKinnon [53], a minimum sample size of 558 participants was targeted. 602 complete data sets were collected. Six participants were excluded because they had not correctly answered the manipulation check, asking which of the four conditions was visible in the stimulus material. In addition, two participants were excluded for not passing the attention check.

The final sample consisted of 594 participants (289 females, 294 males, 11 diverse), aged 18 to 73 (M = 29.74, SD = 8.88). Most participants reported having a high school diploma or higher (87.21%), of which 56.37% had a university degree. Of all participants, 47% had used ChatGPT several times, 23.90% often, 12.10% once, and 17% had never used it before.

4. Results

All analyses were performed with the statistical software Jamovi version 2.3.26.0 and the regression analysis tool PROCESS for R version 4.3.1. Investigating the present hypotheses required the estimation of a serial multiple mediator model corresponding to the PROCESS model 6. The independent variable knowledge domain was dummy coded (0 = *objective*, 1 = *subjective*). A significance level of 5% was chosen for all statistical analyses.

4.1. Descriptive statistics

The descriptive statistics for the variables perceived expertise, perceived risk, trust, perceived usefulness, and use intention, divided by the groups objective (n = 298) and subjective knowledge domain (n = 296) as well as in total, can be found in Table 1.

Table 1. Descriptive statistics.

Variables	**objective knowledge**		**subjective knowledge**		**total**	
	M	***SD***	***M***	***SD***	***M***	***SD***
Perceived objectivity	5.16	1.27	2.85	1.45	4.00	1.79
Perceived expertise	3.66	0.86	3.34	0.83	3.50	0.86
Perceived risk	2.58	0.88	2.48	0.91	2.53	0.90
Trust	3.06	0.52	2.98	0.53	3.02	0.53
Integrity/Process	2.85	0.57	2.73	0.60	2.79	0.59
Benevolence/Purpose	3.33	0.67	3.23	0.73	3.28	0.70
Ability/Performance	3.03	0.59	3.01	0.54	3.02	0.57
Perceived usefulness	3.58	1.05	3.61	1.04	3.60	1.05
Use intention	3.69	1.17	3.71	1.17	3.70	1.17

4.2. Testing the hypotheses

A Pearson product-moment correlation was performed (Table 2). The 95% confidence intervals (CI) of the mediation model were bootstrapped for the indirect effects with the help of 5,000 bootstrap samples.

Table 2. Pearson product-moment correlation.

Variable	1	2	3	4	5	6	7	8
1. Knowledge domain	-							
2. Perceived expertise	-.19***	-						
3. Perceived risk	-.05	-.13**	-					
4. Trust	-.08	.44***	-.33***	-				
5. Integrity/ Process	-.11**	.42***	-.29***	.84***	-			
6. Benevolence/ Purpose	-.08	.33***	-.29***	.85***	.58***	-		
7. Ability/ Performance	-.01	.40***	-.28***	.87***	.62***	.60***	-	
8. Perceived usefulness	.01	.26***	-.20***	.33***	.24***	.31***	.29***	-
9. Use intention	.01	.23***	-.22***	.32***	.27***	.31***	.25***	.73***

The serial multiple mediator model (see Figure 2) comprises one direct and 15 indirect effects of knowledge domain on use intention.

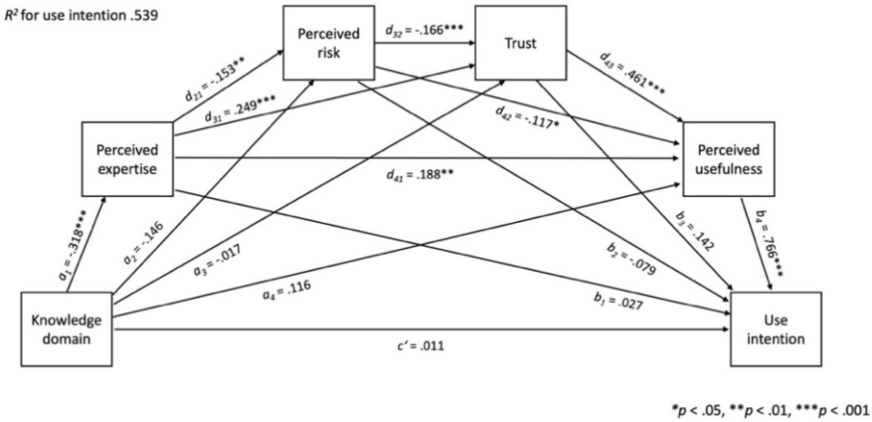

Figure 2. Statistical diagram of the estimated serial multiple mediator model with four mediators.

Knowledge domain has no significant direct effect on use intention, c' = .011, $t(588)$ = 0.16, p = .873. The indirect effect of knowledge domain on use intention mediated via perceived expertise is not significant, a_1b_1 = -.318(.027) = -.009, 95% CI [-0.039, 0.021]. Knowledge domain has no significant indirect effect on use intention mediated via perceived risk, a_2b_2 = -.146(-.079) = .012, 95% CI [-0.002, 0.035]. The indirect effect of knowledge domain on use intention mediated via trust is not significant, a_3b_3 = -.017(.142) = -.002, 95% CI [-0.016, 0.011]. Knowledge domain has no significant indirect effect on use intention mediated via perceived usefulness, a_4b_4 = .166(.766) = .089, 95% CI [-0.032, 0.210]. Therefore, hypotheses 1-5 are rejected.

Knowledge domain has a significant negative indirect effect on use intention mediated via perceived expertise, perceived risk, trust, and perceived usefulness in serial, $a_1d_{21}d_{32}d_{43}b_4$ = -.318(-.153)-.166(.461).766 = -.003, 95% CI [-0.006, -0.001]. The objective domain group perceived higher expertise than the subjective one, which was accompanied by lower perceived risk, which in turn caused higher trust, which produced higher perceived usefulness, and this elicited higher use intention. The research model explains 54% variance for use intention (R^2 = .539). Thus, hypothesis 6 is confirmed.

5. Discussion

5.1. Hypothesis testing and research model

The study aimed to improve the understanding of users' perceptions of chatbots' expertise in different domains and how this influences their use intention, as previous research has primarily focused on the capabilities of the system [7]. For this purpose, it was analyzed how ChatGPT is evaluated in subjective and objective knowledge domains, along with the mediators of perceived expertise, perceived risk, trust, and perceived usefulness. The results show an indirect effect of knowledge domain on use intention through perceived expertise, perceived risk, trust, and perceived usefulness in serial. However, knowledge domain does not have a direct significant effect on use intention, not even via each mediator on its own.

The assumption that knowledge domain has a direct effect on use intention (H1) was not confirmed. There is no significant difference in the use intention for subjective and objective knowledge domains. Thus, the results are discrepant with the numerous findings that use intention is higher regarding objective knowledge domains compared to subjective ones [8]. Future studies need to analyze whether this might be due to the fact that an interface with multiple social cues such as ChatGPT is also trusted with subjective tasks unlike in other human-algorithm interactions. However, the established model shows that knowledge domain still has an indirect influence on use intention via the distinct path of influencing perceived expertise, risk, trust and usefulness (H6).

Contradicting hypothesis 2, there is neither an effect of knowledge domain on use intention mediated by perceived expertise, nor a direct effect of perceived expertise on use intention. Nevertheless, it plays a role in the perception of chatbots in different knowledge domains, as perceived expertise is significantly higher in tasks of objective knowledge domains than in subjective ones. This supports the idea that individuals believe algorithms are more capable of handling mechanical and objective tasks than subjective ones, leading to higher aversions and a decreased likelihood of entrusting them [8,9], while preferring a human for subjective knowledge domains [24]. Also, the present results show that higher perceived expertise leads to increased trust in chatbots, highlighting its relevance in the trust building process [54]. Similarly, perceived expertise enhances perceived usefulness and reduces perceived risk, supporting previous results [29].

Perceived risk does not mediate the effect of knowledge domain on use intention and there is no direct effect of perceived risk on use intention, contradictory to previous studies showing a direct influence [29,39] and to hypothesis 3. Nevertheless, the present study showed that higher perceived risk leads to lower perceived usefulness, which in turn influences use intention, consistent with Lu et al. [55]. Accordingly, a low perceived risk by itself does not seem to be sufficient to influence the intention to use chatbots. Rather, risk-related variables such as trust seem to affect the use intention. The importance of trust in the use of technology is highlighted by the perceived risks associated with its use in a given context [12]. Perceived risk thus appears to be a relevant factor that may not have a direct, but an indirect effect on use intention via further variables such as perceived usefulness and trust.

Hypothesis 4 is rejected since trust does not mediate the effect of knowledge domain on use intention. Despite the absence of a direct effect of the knowledge domain, trust was significantly higher for the objective than the subjective knowledge domain, confirming our assumptions and in line with Castelo et al. [10]. Considering the subscales of trust, it is noticeable that only the subscale integrity/process correlates with knowledge domain and thus seems to play a more important role than benevolence/purpose and ability/performance. Therefore, whether ChatGPT meets the standards seems to be related to the knowledge domain, as higher integrity/process is perceived in the objective one. In contrast, the qualities and attributed intentions seem to be not related to whether a task belongs to the subjective or objective knowledge domain. It should be further investigated why these two trust dimensions play a subordinate role in chatbots or whether the results are due to the lack of direct interaction in the present study.

The results show that trust has no direct influence on use intention, contradicting previous studies (e.g. [11]). Nevertheless, there is an indirect effect of trust on use intention, mediated by perceived usefulness, supporting previous results [56]. It appears that it is not sufficient to trust chatbots to develop an intention to use it. Instead, there must be a perceived benefit for people to want to use them.

The assumption that the effect of knowledge domain on use intention is mediated by perceived usefulness (H5) is not confirmed. Apparently, the knowledge domain has no direct influence on perceived usefulness. However, it was shown that perceived usefulness has a significant effect on use intention, confirming the results of previous studies [18–20]. Kang and Hwang [57] showed that the effect of personalization and interactivity on continuous use intention is mediated by perceived usefulness. This indicates that other aspects such as the characteristics of the application may be relevant. As there is no difference between the objective and subjective knowledge domain, it can be assumed that usefulness is assessed by the characteristics of ChatGPT. Yoon et al. [58] found that technical characteristics have an impact on perceived usefulness, which in turn forms the behavioral intention to use. Further, they showed that perceived usefulness is also affected by individual characteristics and social influence factors. Our results are consistent with the TAM, as perceived usefulness has a significant effect on use intention and is thus a determinant of behavioral intention to use technology. Ghazizadeh et al. [47] added trust in the TAM, showing a positive effect on perceived usefulness, which in turn positively influences use intention. The present study supports these findings and extends them by relating this path to knowledge domain and its influence on perceived expertise and perceived risk.

The results of the mediation model show that the influence of the knowledge domain occurs serially via the mediating variables perceived expertise, perceived risk, trust, and perceived usefulness, confirming hypothesis 6. This shows that it is not the knowledge domain alone that determines whether chatbots are intended to be used in a certain domain, but how much expertise is attributed to the chatbot in this area, how high the risk is to use the provided information, how much a person trusts chatbots in this area, and whether it promises added value. The model significantly predicts the use intention of chatbots with 54% and confirms that perceived expertise is an important factor in the formation of trust [9], differing in objective and subjective knowledge domains. Furthermore, the results support the assumed sequence of variables and the effects of these on each other [19]. Perceived expertise has an effect on perceived risk, and relying on expertise that is falsely perceived to be of high quality appears to pose greater risks in some knowledge domains than in others [10]. Perceived risk is a predictor of trust, as individuals are more cautious in their use when the likelihood of negative consequences is high, confirming previous studies [12,13,59,60]. The results show that trust in a technology has a positive effect on perceived usefulness, supporting previous findings [14,15]. Finally, it is also shown that perceived usefulness has an influence on use intention, which is consistent with prior research [27,47].

5.2. Implications

The current study provides evidence that it is insufficient to examine isolated variables for insights into the intention to use and actual use of technologies like chatbots. The relevance of taking a closer look at the dynamics of multiple variables becomes clear when considering the study results. Along with this, it was shown that established theoretical models like the TAM [27] alone may no longer be sufficient to represent the complex psychological mechanisms that influence whether people want to use a technology. Similar to Ghazizadeh et al. [47], who added trust to the original TAM [27], the present results suggests that an integration of additional variables, such as perceived expertise and perceived risk, may be necessary to obtain a comprehensive understanding of the use behavior. The results contribute to the discussion whether knowledge domains are important for the emergence of algorithm appreciation or algorithm aversion [8].

With regard to practical implications, the results imply that people are aware that for some tasks the usage of ChatGPT might be more reasonable than for others. Moreover, it becomes apparent that handling chatbots' responses must be learned and, in addition to the benefits, the potential risks and limitations should be explained [61].

5.3. Limitations and future research

The present study simulated an interaction with ChatGPT so that all subjects within the condition were shown the same question and answer. This has the advantage of comparability of results but the external validity might be limited – specifically as only two tasks were included. In addition, it must be emphasized that the scenarios were predetermined, and the subjects may not have had actual interest in asking the used questions. Although the instructions indicated that the questions refer to the use of ChatGPT in the specific knowledge domain, it cannot be excluded that the use of ChatGPT, in general, was considered when answering. This is particularly relevant since it is a new technology that can be used for different purposes.

The predicted variance of intention to use is good at 54% [62] but needs further research to determine what additional factors affect the intention to use ChatGPT. A relevant factor that was not examined in this study due to the lack of interaction is perceived ease of use [18,47,63]. Since perceived ease of use can have a positive influence on the favorable impression of a technology [63] and trust [11,64], it can potentially influence psychological processes associated with the intention to use chatbots. Therefore, its role in the mediation model should be investigated.

Furthermore, future studies should try to investigate an interactive use of chatbots to explore not only the intention to use but also the actual use of the chatbot. Different contexts of use beyond the task should also be considered here, as it could play a role in whether chatbots are used for personal, academic or work-related purposes. It can be expected that perceived expertise and perceived risk as well as trust, perceived usefulness and use intention vary regarding different contexts of work or personal application [65,66].

5.4. Conclusion

The study complements previous research findings on the use of technologies, in particular ChatGPT. The results show that the interaction of different variables influences the use intention, and that the consideration of individual factors alone is not sufficient. It could be shown that perceived expertise plays a central role in the use of chatbots in different knowledge domains, as individuals would be more likely to attribute the ability to answer objective rather than subjective tasks to the system. Perceived expertise also influences the perceived risk, trust, and perceived usefulness and thus contributes to the use intention. This leads to the conclusion that it is not the danger of potentially illogical or misleading material that decides whether chatbots will be used, but rather how much expertise and credibility is assigned to the chatbot in this area. Furthermore, the results of the current study indicate that individuals would rather use chatbots for retrieving pure information and facts but have less faith in the system for creative activities or those involving a higher degree of interpretation.

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