Cureus Journal of Computer Science

Open Access Original Article

Exploring AI Chatbot Adoption for Knowledge Workers: A Unified Theory of Acceptance and Use of Technology Extension

Received 07/02/2025
Review began 07/28/2025
Review ended 09/03/2025
Published 09/11/2025

DOI:
https://doi.org/10.7759/s44389-025-07459-9

Filippo Bianchini [1] , Alessio M. Braccini [2] , Francesca De Luzi [1] , Mattia Macrì [1] , Massimo Mecella [1]

1. Department of Computer, Control and Management Engineering "Antonio Ruberti" (DIAG), Sapienza University of Rome, Rome, ITA 2. Department of Economics Engineering Society and Organization – DEIM, University of Tuscia, Viterbo, ITA

Corresponding author: Filippo Bianchini, bianchini@diag.uniroma1.it

Abstract

AI chatbots have emerged as transformative tools in knowledge-intensive work environments. While existing research largely focuses on AI chatbots as interactive agents in customer service or their capability to replace human labor, fewer studies have examined their adoption from the perspective of knowledge workers. Literature has explored users' intention to adopt AI chatbots using Unified Theory of Acceptance and Use of Technology (UTAUT), yielding contradictory results. In this paper, we extend UTAUT by introducing new factors not previously addressed in the literature. Our results support existing empirical evidence and confirm that core UTAUT constructs, excluding performance expectancy, do not influence attitudes toward use, while further demonstrating that they positively impact users' attitudes toward innovating with AI, which emerges as a new antecedent to intention to use. Furthermore, our findings highlight the role of critical thinking as a counterbalance to the perceived risks of using AI chatbots, an aspect that literature suggests can undermine intention to use. Finally, we explore task characteristics, identifying teamwork as positively influencing both attitudes toward innovating and intention to use. These findings indicate that chatbot adoption among knowledge workers is more complex than depicted by UTAUT and is shaped by both personal perceptions and the broader work environment. Our work provides practical insights for organizations aiming to integrate AI chatbots into professional settings, as well as theoretical implications. Limitations include the narrow variety of domains addressed.

Categories: Ethical and Social Implications, AI applications
Keywords: working with ai, chatbot adoption, knowledge workers, utaut, pls

Introduction

The development of Artificial Intelligence (AI) has seen chatbots as one of the most significant recent advancements [1,2]. Chatbots generate coherent and contextually relevant responses based on user inputs. Chatbots leverage Large Language Models (LLMs), AI models designed for data generation, unlike traditional AI models, focused on prediction and classification [3]. AI chatbots use cognitive frameworks providing valuable answers to users' queries [1]. Chatbots assist in knowledge manipulation and are increasingly adopted by businesses, suggesting transformative implications for work environments [2,4,5]. While various studies have explored the factors influencing user adoption of AI chatbots [6,7], empirical research remains limited and often focused on specific areas [8].

Research primarily examines AI chatbots as interactive agents in customer interactions, assessing their ability to alleviate or replace human labor [9,10] and the perception of chatbots as anthropomorphic or capable substitutes for human roles [2,6,11-13]. However, empirical evidence on the use of generative AI shows that interactive usage with human actors is more prevalent than automation application [14]. Additionally, studies have explored some factors influencing user perception and intention to use chatbots [15-17], but research on contextual factors related to the perception of the technological artifact remains underexplored [6]. Finally, while the literature acknowledges AI chatbots for their ability to assist in knowledge-intensive tasks [16,18-21], there has been less focus on human-AI interaction in knowledge generation.

This paper aims to fill these gaps by viewing chatbots as tools for text manipulation, not just as interactive agents. Our focus shifts to knowledge workers, i.e. individuals collaborating with AI in knowledge-related tasks. Instead of studying people's perceptions when AI replaces workers, we focus on knowledge workers working with AI. We will analyze user traits and task characteristics to understand contextual factors affecting chatbot usage intentions. We specifically target knowledge workers engaged in complex tasks prioritizing problem-solving and critical thinking [22]. While some initial research exists on knowledge workers using chatbots [23], overall empirical research is still nascent [8].

How to cite this article
Bianchini F, Braccini A M, De Luzi F, et al. (September 11, 2025) Exploring AI Chatbot Adoption for Knowledge Workers: A Unified Theory of Acceptance and Use of Technology Extension. Cureus J Comput Sci 2 : es44389-025-07459-9. DOI https://doi.org/10.7759/s44389-025-07459-9

Our study integrates the Unified Theory of Acceptance and Use of Technology (UTAUT) with new constructs to explore user attitudes towards chatbot usage. Data from knowledge workers across various domains will be analyzed using Partial Least Squares/Structural Equation Modelling (PLS-SEM), focusing on the widely recognized ChatGPT as our artifact. The paper is driven by the following research questions:

RQ1: *What factors influence knowledge workers' intention to use AI chatbots?*

RQ2: *How the individual, organizational, and task context impact knowledge workers' intention to use AI chatbots?*

Conceptual framing

In this paper, we focus on AI chatbots as knowledge technology and explore factors affecting knowledge workers' intention to use such tools in their tasks. To this end, our work is conceptually framed around the exploration of AI chatbots as the focal artefact and users' perceptions in their interaction with AI chatbots. The relevant literature on these two aspects will be presented and discussed in the following sub-sections.

AI Chatbots

AI chatbots represent a significant achievement in AI [2], possessing substantial transformative potential for workers and organizations [24]. With a history spanning several decades that traces back to the early days of statistical natural language processing [21], chatbots have evolved considerably. In the past, they were rule-based and exhibited limited capabilities [25]. Today, advanced machine-learning algorithms have enhanced their ability to understand and generate natural language, allowing for engaging conversational interactions with users [26]. Machine learning has enabled chatbots to learn from data and enhance their responses over time [3,15,27]. Modern AI chatbots are sophisticated tools that can simulate conversations with humans through text or voice interactions. They have found many uses in communication, automation, and customer support [28]. Many hi-tech companies have developed their LLMs for years, employing various approaches and target features. Drawing a state-of-the-art comparison is challenging, as evolution is vigorous, with new and improved chatbots frequently released. GPT-3, from OpenAI, is widely regarded as the first LLM to demonstrate emergent abilities not present in previous models. GPT-4, 4o, o1, and o3 are the most recent versions of the model released by OpenAI. Anthropic developed Claude, targeting the creation of safer models with minimum human intervention during the training phase [29]. LLaMA is an entirely open-source collection of foundational language models released by Meta. Despite the smaller size of its models compared to the GPT family, LLaMA has shown state-of-the-art performance on various benchmarks [30]. Google developed the Pathways Language Model architecture, paying particular attention to the results achieved using few-shot learning techniques [31] and being the first to implement a continuous training approach [32].

AI chatbots offer various capabilities, and promise several advantages. However, their use is not without risks. AI technology raises concerns due to its significant transformative implications [2] and its rapid development [33]. Many individuals perceive AI as possessing an independent identity, prompting questions about autonomy and decision-making [34-36], with some considering AI as a threat to employment opportunities for administrative and knowledge-based workers [37]. Since perception influences the intention to use and actual usage, it is crucial to explore users' perceptions of AI chatbots and their intentions to use them. Furthermore, AI systems generate outputs based on extensive datasets and stochastic methods, rendering their results not always easily explainable [37] or accurate [3].

Users' Perception of AI Chatbots

Exploring users' perceptions is a well-established research approach in the IS literature to understand users' intentions to adopt specific technologies. IS literature already explored users' perception of AI chatbots and encourage further empirical and theoretical investigations [8,28]. A significant portion of the IS literature examines AI chatbot as interactive agents [28,38] and investigates how the perception of the presumed anthropomorphic traits of chatbots influences users' intentions to adopt the chatbot during a particular interaction. The types of interactions most frequently studied pertain to customers receiving recommendations or engaging with automated online services [9,16,28,38-40]. Less commonly, literature examines interactions in decision-making [10] and in learning and education [28].

A significant area of focus in the literature pertains to the anthropomorphic perception of the targeted user and its consequent impact on their intended or actual behavior. The literature clarifies that behavior changes when users believe they are interacting with an AI chatbot rather than a human [10,16,40]. The perception also alters when the interaction involves a combination of human and AI chatbot agents operating behind a single interface [39], or when users recognize that their interaction is occurring with a chatbot instead of a human [41]. The anthropomorphism of AI chatbots is a recurring theme in this area of literature even in studies that do not specifically focus on this aspect, but examine how the perception of certain human traits, such as verbal and non-verbal emotional expressions [10], empathy, or curiosity [42], as well as variable responses [15], impact users' behavior.

Other studies have explored the potential roles of AI chatbots, emphasizing their features as knowledge and automation technologies [38], support technologies for decision-making [10], and tools for learning [28]. In the academic realm, investigations focus on the role chatbots might play in research peer review [24], the ethics surrounding their use [43], and their effectiveness in education [44]. A few studies mention the knowledge aspects related to chatbots, which, due to the underlying LLM technology, can capture expert knowledge and generate insights that mimic experts [16]. Complementing this perspective, several sources recognize the capability of chatbots to function as collaborative entities with which users can engage in the process of creating knowledge content [43] or to operate similarly to a co-worker [38].

Research Gap

The current literature examining AI chatbot adoption has revealed substantial theoretical insights into the factors influencing both the intention to use and the actual usage of chatbots. Simultaneously, it is evident that there are gaps in the research concerning AI chatbots.

Firstly, current literature on AI chatbots strongly emphasizes the exploration of the perceived human characteristics of chatbots and their implications for users' behavioral intentions or actual usage in settings in which AI replaces or sides humans [2,38]. Although this research has faced criticism for yielding inconsistent findings, particularly regarding the emotional dimension of AI chatbot usage [10], it has also clearly established that users' perceptions significantly affect their behavioral intentions and actual usage and that this perception can be influenced by multiple factors [39]. However, insufficient attention has been directed towards users' perceptions of chatbots as tools for knowledge generation activities.

Secondly, while examining users' perceptions of AI chatbots as interactive agents, the literature has primarily concentrated on factors such as demographics, motivations, social influence, and technological benefits to investigate usage intentions [28]. However, minimal attention has been given to examining contextual factors, particularly concerning the knowledge task and its characteristics. Ultimately, although chatbots can be employed in knowledge-related activities, there has been limited research that investigates this particular context and examines knowledge workers' perceptions of collaborative interaction with AI chatbots.

Researchers consistently utilized established theoretical frameworks such as the UTAUT/UTAUT2 [45] and technology acceptance model [46] to analyze AI chatbots, complementing these models with new constructs and hypotheses [47,48]. Empirical research on interactions with AI chatbots remains nascent [8], and the literature continues to seek alternative theoretical explanations for usage intention [28].

Theoretical framing

In this paper, we contribute to the IS literature by exploring new factors that explain knowledge workers intention to use chatbots for their knowledge tasks. To achieve this, we begin with UTAUT, an established theoretical framework in IS that is frequently used to explore users' perceptions of technology.

The UTAUT was developed in 2003 by Venkatesh et al. [49] and updated in 2012, aiming to measure the likelihood of success for new technologies and to understand the factors influencing acceptance. Drawing upon several pre-existing theories, such as the *Theory of Reasoned Action*, the *Theory of Planned Behavior*, and the *Technology Acceptance Model*, UTAUT amalgamates their perspectives [50]. Regarding acceptance models, the technology acceptance model, initially proposed in 1989 by Fred Davis [51], emphasizes perceived ease of use and perceived usefulness as primary determinants of user acceptance. However, as technological landscapes evolve, UTAUT provides a more comprehensive perspective by integrating factors such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SN), and Facilitating Conditions (FC). By doing so, UTAUT offers a holistic framework for understanding technology acceptance and usage.

UTAUT has already been employed to study emerging AI tools, such as chatbots [6], virtual assistants [52], recommender systems [53], and predictive analytics tools [54]. Additionally, it has been utilized to explore the impact of AI technologies on early adopters [55,56]. Literature returns contradicting results, with empirical analysis confirming the validity of the UTAUT framework, or indicating lack of support for key factors [8,57].

UTAUT is based on four key constructs: PE, EE, SN, and FC. These constructs provide a framework for understanding technology adoption by emphasizing the technological and organizational factors that affect user behavior. In this work, we enhance this theoretical framework with new concepts to offer a more comprehensive perspective on knowledge workers': Critical Thinking (CRI), Team Working (TWO), Perceived Risk (PRI), Type of Task (TT), Level of Interaction (LI), and Attitude Towards Innovating (AU).

Critical Thinking (CRI)

CRI involves a critical understanding, evaluation, and interpretation of information. This trait is essential for knowledge workers. Some studies have explored how chatbots influence users' CRI, especially in academic knowledge work [58]. However, literature has not explored CRI as a precursor to users' behavioral intention to use AI chatbots. AI chatbots, based on LLM technologies, are notorious for producing inaccurate and contextually irrelevant content in response to the inputs provided [8]. Specifically, GPTs are not known for their veracity [20]. Indeed, they are notorious for phenomena such as hallucination, which leads them to generate false information [59]. The same technology producers acknowledge that it "may be inaccurate, untruthful, and otherwise misleading at times" [3] and continually work in improving their products. Untrustworthiness of contents produced has already been found associated with reduced intention to use [60-62]. Given that end users have limited possibilities of ensuring the veracity and truthfulness of AI chatbots, they must rely on their ability to critically interpret the outputs produced. Therefore, we include this construct in our model to assess whether the practice of evaluating the credibility and accuracy of the output obtained from a chatbot can influence behavioral intention.

H6a: *Users' Critical Thinking positively impacts the Behavioral Intention to use AI chatbots.*

Attitude Towards Innovation (AU)

Chatbots are the last recent innovation in AI [2]. In many fields, including that of knowledge work, the use of AI chatbots is considered an innovation. AU with AI chatbots may impact the intention to use AI chatbots. For instance, users' attitudes within other forms of innovation in the organization positively impact the behavioral intention to use AI-integrated CRM in organizations [12]. In general, individuals' attitudes toward an object have been recognized as a direct antecedent of their behavioral intention to use [63]. Furthermore, attitudes toward AI predict the intention to use the technology [64]. Considering that interaction with AI chatbots is individual, we expect the personal innovativeness traits of the adopting individual to impact adoption [16]. Consequently, this work includes AU to explore knowledge workers' individual predisposition to adopt an innovative technology and its impact on knowledge workers' behavioral intention to use AI chatbots.

H5: *The users' Attitude Toward Innovating organizations with AI chatbots positively impacts their Behavioral Intention to use AI Chatbots.*

Team Working (TWO)

The literature acknowledges that AI chatbots possess significant transformative potential for individuals and organizations [2,24]. For instance, in the context of teamwork, Susa [65], a conversational agent, was employed to facilitate teamwork and collaborative practices. Additionally, the authors provide new insights into the acceptability and usability of conversational agents in promoting teamwork and collaborative practices in the workplace. However, the literature exploring AI chatbots focuses on individual interactions with the technology [39]. Few studies explore if team dynamics impact intention to use. We hypothesize that, in the context of knowledge workers, interactions among team members may influence the intention to use AI chatbots or attitudes towards adopting these innovations in their work.

H7a: *Team Working positively impacts the Behavioral Intention to use AI Chatbots.*

H7b: *Team Working impacts the Attitude Towards Innovating of users.*

Perceived Risk (PRI)

PRI refers to the anticipation of potential issues arising from the introduction of technology or methods. Research demonstrates how PRI adversely affects intention to use [66]. As previously mentioned, the literature expresses concern about the risks associated with the use of AI chatbots [21,20] and the fact that users might not be aware of these risks [3]. Indeed AI chatbots are trained with specific types of data (such as social media and other sources) yet applied across various purposes and domains (e.g. research, law, consultancy) introduces significant risks regarding the use of this technology in knowledge activities [21], particularly when they serve as assistants in knowledge creation [20]. Some sources also suggest that the perception of AI chatbots as untrustworthy may discourage knowledge workers from adopting them [8,60-62]. Risks such as privacy concerns, veracity of information produced, and fear of misinformation are frequently cited by the literature [3,8,20].

H8a: *Perceived Risk negatively impacts the Behavioral Intention to use AI Chatbots.*

H8b: *Perceived Risk negatively impacts the Attitude Towards Innovating of users*.

Instead, we believe that the ability to critically evaluate the output of AI chatbots, as assessed by CRI, may positively influence the awareness of risks associated with AI chatbot usage among knowledge workers.

H6b: *Critical Thinking positively impacts the Perceived Risk of users.*

Type of Task (TT)

AI chatbots can serve various knowledge tasks as a form of knowledge manipulation technology [20,21]. However, the existing literature has not investigated the impact of task type on users' intention to utilize AI chatbots. With the TT, we aim to measure the nature of the activities performed by knowledge workers. This factor is assessed through a series of questions that explore the types and characteristics of the activities described. Considering that AI chatbots can be used both to automate and augment tasks [38], and taking into account the role that routine and research play in organizational activities as noted in the organization studies literature [67], we seek to determine whether the activity is routine, involves research, or requires creativity. The goal is to understand the level of complexity and variety in activities that influence the use of AI chatbots.

H9a: *Type of Task positively impacts the Level of Interaction among users.*

We also hypothesize that activities requiring a high level of creativity and group interaction will foster teamwork, stimulating collaboration and idea exchange among team members.

H9b: *Type of Task positively impacts the Team Working through users*.

Level of Interaction (LI)

This construct refers to the degree of interaction that an individual has with others during knowledge tasks, assessed across various levels. We conceptualize knowledge workers as not working in isolation but engaging collaboratively within teams. Consequently, we incorporate different types of interactions among tasks and knowledge workers into our model. We reference a typology of interaction activities well recognized in organizational studies literature [68], which distinguishes between sequential, aggregational, and group activities, to which we also add the individual dimension. The aim is to evaluate how the type of interaction a knowledge worker has with other knowledge workers during task execution can influence teamwork and, consequently, the adoption and use of AI chatbots by those workers, thereby indirectly affecting the behavioral intention to use them.

H10: *Level of Interaction positively impacts the Team Working through users*.

Research Model

The previously described constructs complement the established constructs of the UTAUT model: PE, EE, SN, and FC.

PE and EE represent users' expectations regarding how technology will enhance their job performance and the ease of its use. The functionality of AI chatbots has been found to correlate with usage [28]. In line with this, we hypothesize that the PE associated with using AI chatbots influences the intention to use the chatbot and adopt innovation.

H1a: *Performance Expectancy positively impacts the Behavioral Intention to use AI Chatbots*

H1b: *Performance Expectancy positively impacts the Attitude Towards Innovating of users.*

EE pertains to the perceived ease of using new technology. The literature does not consistently demonstrate a positive effect of EE on the intention to use [57,69]. Consequently, we hypothesize that EE affects the intention to use chatbots and the individual AU.

SN refers to the impact of others on an individual's adoption of a specific technology [49]. In general, users are inclined to conform to social group norms when deciding on the use of AI [70,71]. However, previous studies on AI chatbots suggest that SI can have both positive and negative effects on users' intention to use the technology. Hence, we hypothesize that SN has an impact on the intention to use AI chatbots and in the attitude towards adopting these innovations.

H3a: *Social Influence positively impacts the Behavioral Intention to use AI chatbots.*

H3b: *Social Influence positively impacts the Attitude Towards Innovating of users.*

Finally, we include FC to assess the impact of a potentially existing organizational or technical infrastructure - including technical resources and skills - to support knowledge workers in using technology on their intention to use AI chatbots.

H4: *Facilitating Conditions positively impact the use behavior to use AI Chatbots*.

Our final research model, shown in Figure *1*, includes the organizational context (through SN and FC), the individual context (through PRI, AU, and CRI), and the task context (through TWO, LI, and TT). Even though not visualized in Figure *1*, our model includes gender, age, and experience as moderators from the original UTAUT model. We added the domain to measure the potential impact of our knowledge workers' different professional sectors. We also dropped voluntariness - another original UTAUT model moderator - since our data collection took place in trials in which users were asked to use the technology.

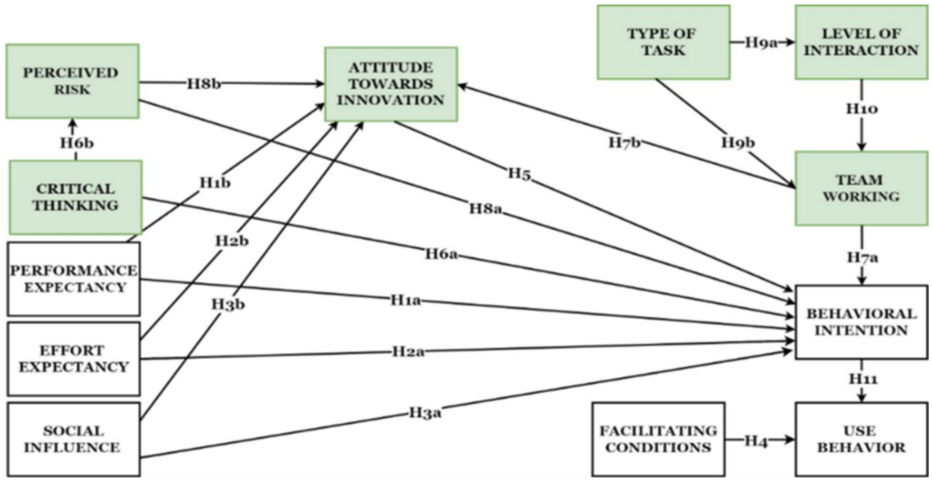

FIGURE 1: Research model and hypotheses

Adapted from Venkatesh et al. [49].

The white rectangles represent the constructs already present in the Unified Theory of Acceptance and Use of Technology model, while the light green rectangles are the new constructs we added for this study.

Materials And Methods

In this paper, we use PLS-SEM to analyze the determinants of knowledge workers' behavioral intention to use AI chatbots. The data were analyzed using SmartPLS 4. Analysis was conducted with the standard PLS-SEM algorithm, yielding standardized results.

Research design

Data Collection

This study involved 320 participants: 132 females (41%) and 188 males (59%), aged between 19 and 50 years. The dataset used in this study was created from scratch between March 2024 and June 2024, tailored to meet the specific requirements of the proposed research framework. All participants are knowledge workers engaged in knowledge-intensive, problem-solving, and creative activities across three different domains. The subjects recruited for the analysis came from these domains: i) public sector, specifically the Italian judiciary system (60 participants); ii) digital content production and web design (77 participants); and iii) public education sector, which includes students and doctoral candidates in management (183 participants). All groups share a basic understanding and use of AI chatbots, particularly ChatGPT, without requiring advanced technical computer skills. Participants were recruited during seminars on AI, specifically focusing on the usage of AI chatbots and prompt engineering techniques. Briefed on data confidentiality and the research objectives, participants contributed as anonymous voluntary informants for data collection, ensuring their informed consent. Table *1* summarizes the composition of our sample.

Demographics		Frequencies (M–F)	Percentage (M–F)
Gender	Male	188	59%
	Female	132	41%
Age	19-22	126 (70–56)	39% (56–44%)
	23-26	119 (72–47)	37% (60–40%)
	27+	75 (46–29)	24% (61–39%)
Domain	Public sector - Italian judiciary system	60 (34–26)	19% (57–43%)
	Digital content production and web design	77 (37–44)	24% (48–52%)
	Public education - Management field	183 (117–66)	57% (64–36%)

TABLE 1: Sample composition

Questionnaire

To collect data, we used an online survey structured in five sections, administered on the JotForm platform:

Section 1: Providing a brief overview of the Chatbot AI under investigation, emphasizing its functionalities and capabilities with examples of prompts to accomplish various tasks.

Section 2: It compiled demographic data from participants, including gender, age, email, and working domain. The domain information has been utilized to introduce the new moderating factor, Domain (DOM). To ensure the reliability of the data, this section included two qualifying questions (EXP1, EXP2). These questions aimed to determine participants' familiarity with AI chatbots (*Yes* or *No*), such as ChatGPT, and how often they used them (*Never*; *Sometimes*; *Often*; *Every Day*). Table 2 summarizes the results of the aforementioned qualifying questions.

Qualifying questions	Answer	Frequencies (M–F)	Percentage (M–F)
EXP1 - Do you know any AI chatbots (such as ChatGPT)?	Yes	309 (182–127)	97% (57–43%)
	No	11 (6–5)	3% (55–45%)
EXP2 - How often do you use AI chatbot (such as ChatGPT)?	Never	38 (19–19)	12% (50–50%)
	Sometimes	180 (105–75)	56% (58–42%)
	Often	92 (56–36)	29% (61–39%)
	Every day	9 (7–2)	3% (78–22%)

TABLE 2: Qualifying questions

Section 3: In this section, participants were required to provide a qualitative description of the primary activities undertaken with an AI chatbot in their knowledge work. The qualitative data collected in this section were manually categorized in (1) text generation, (2) information extraction, and (3) code generation. These categories were coded in three formative 0-1 dummy indicators (TASK1, TASK2, TASK3) for the new formative construct referred to as *Type of Task*. Section 3 also outlined the characteristics of activities conducted with the aid of an AI chatbot, which are indicated by three indicators (USE1, USE2, USE3) of the formative construct Use Behavior (USE). A final question examined the Level of Interaction involved in the activities performed. The responses to this last question, which offered three possible options-individual, sequential, and group-have been disaggregated into three 0-1 dummy indicators (LI1, LI2, LI3) for the new formative construct known as Level of Interaction. In the analysis, the first indicator L1, corresponding to individual response, has been excluded, serving as the reference category to explain the effects of the others.

Section 4: participants are tasked with responding to a series of questions pertaining to the presented topic. A total of 48 questions are included, all requiring evaluation on a LIKERT scale ranging from 1 to 5, where represents *Strongly disagree* and represents *Strongly agree*. These questions are presented in varying formats and are randomized for each participant in the study

Results And Discussion

In this section, we analyze our measurement and structural models. We outline the evaluation criteria employed to assess the effectiveness of our research model, providing insights into how well it captures the relationships between constructs. Additionally, we present the outcomes of these analyzes, offering a clear perspective on our model's performance in explaining the phenomena under investigation.

Measurement (inner) model

Reflective Construct

When assessing the measurement model, following what suggested by Hair and Alamer [72], our analysis began with an examination of the reflective construct, starting from the outer loadings to gauge the validity of individual indicators against specific criteria:

(1) we utilized a validity threshold of 0.708, as recommended by the literature [73];

(2) for indicators falling below 0.708 but above 0.400, we evaluated the resulting increase in Average Variance Extracted (AVE) after their removal [72].

In Table *3* are reported all significant indicators from our study: it is worth noting that each one's outer loading falls within the range of 0.701 to 0.909.

Reflective latent construct	α	CR (ρ_α–ρ_c)	AVE	Items	Outer loadings
Performance Expectancy (PE)	0.804	0.827–0.884	0.717	PE1, PE2, PE3	0.887, 0.818, 0.834
Effort Expectancy (EE)	0.751	0.754–0.842	0.573	EE1, EE2, EE3, EE4	0.755, 0.733, 0.808, 0.728
Social Influence (SN)	0.710	0.738–0.872	0.773	SN3, SN4	0.909, 0.848
Facilitating Conditions (FC)	0.767	0.786–0.864	0.680	FC1, FC2, FC3	0.769, 0.872, 0.829
Attitude Towards Innovating (AU)	0.851	0.857–0.899	0.691	AU1, AU2, AU3, AU4	0.820, 0.792, 0.836, 0.875
Critical Thinking (CRI)	0.643	0.695–0.801	0.575	CRI3, CRI4, CRI5	0.843, 0.701, 0.721
Team Working (TWO)	0.792	0.793–0.857	0.545	TWO1, TWO2, TWO3, TWO4, TWO6	0.735, 0.750, 0.741, 0.733, 0.731
Perceived Risk (PRI)	0.725	0.760–0.840	0.637	PRI1, PRI5, PRI6	0.809, 0.833, 0.750
Behavioral Intention (BI)	0.694	0.696–0.830	0.620	BI1, BI2, BI3	0.823, 0.773, 0.766

TABLE 3: Summary of construct reliability and validity measures

AVE, Average Variance Extracted; CR, Composite Reliability

We analyze the internal consistency reliability of the construct. This evaluation utilizes Cronbach's alpha (α) and Composite Reliability (CR), both ρα and ρc. A threshold of 0.70 for each measure is widely accepted and commonly applied in PLS-SEM research. For Cronbach's alpha, acceptable values must be greater than 0.60 but below 0.95 [72].

The AVE measures the extent to which items of a specific construct positively correlate and share a notable degree of variance. A general guideline suggests that values of 0.50 or higher indicate convergent validity of the construct. Mathematically, a value of 0.50 implies that the mean factor loadings of the items are 0.708 or greater, thereby affirming a significant relationship between the variances of the items and their underlying construct [73]. In our study, all items satisfy the thresholds of α, CR, and AVE. Just one indicator (CRI4) shows a loading level slightly lower compared to the threshold (0.701 vs 0.708) that we decided to retain given the overall values of all the metrics in Table *3*.

The final step involves assessing discriminant validity using the Hetero Trait-Mono Trait ratio. This metric evaluates how distinct the construct is from others in the study conceptually. A conservative threshold of <0.85 can be applied, while a more lenient upper limit of 0.90 is also acceptable [72]. In our study, all Hetero Trait-Mono Trait values fall below 0.85, except for the correlation between Behavioral Intention (BI) and AU, which slightly exceeds the threshold at 0.869.

Formative Construct

Once the analysis of reflective constructs is completed, Hair and Alamer [72] suggests proceeding with the evaluation of formative constructs. We explored Collinearity, with the recommended metric being the Variance Inflation Factor (VIF). According to Diamantopoulos and Siguaw [74], VIF values of 5 or higher suggest significant collinearity issues among the predictor constructs, while values below 3 indicate no collinearity. Values between 5 and 3 may be considered acceptable with theoretical justification. In our study, all VIF values range from 1.047 to 1.933, confirming the absence of collinearity among the predictor constructs. The second evaluation pertains to the robustness of the observed variables in contributing to and forming the construct, following two criteria:

(1) analyzing the outer weights of the indicators in the formative construct by using the p-value, which must be <0.05 [72];

(2) evaluating the external loadings of indicators as supplementary confirmation, referencing the threshold discussed in the previous sub-section.

In our case, all indicators in the formative construct (TT, LI, and USE) have $p < 0.05$, indicating their significance, although not all outer loadings exceed 0.400. The results of the VIF and outer loading are detailed in Table *4*.

Formative latent construct	Item	VIF	Outer weights (p-value)
Type of Task (TT)	TASK1, TASK2, TASK3	1.047, 1.025, 1.072	0.568 (0.005), 0.690 (0.000), 0.707 (0.013)
Level of Interaction (LI)	LI1, LI2	1.396, 1.390	1.079 (0.000), 0.983 (0.000)
Use Behavior (USE)	USE1, USE2, USE3	1.562, 1.933, 1.670	0.480 (0.000), 0.379 (0.000), 0.331 (0.000)

TABLE 4: VIF and outer weights for formative constructs

VIF, Variance Inflation Factor

Structured (inner) model

Concerning the structural component of the model (structural or inner model), Hair and Alamer [72] recommend following several steps during this phase. Firstly, the assessment of collinearity is crucial to ensure there is no significant correlation among the constructs. Applying the same criteria used for formative variables, all constructs in our case exhibit VIF values ranging from 1.000 to 2.544, confirming the absence of collinearity. Moving on to path coefficients (β), these illustrate the magnitude and direction of the effect between constructs. Ranges from 0 to 0.10 indicate weak effects, from 0.10 to 0.30 indicate modest effects, from 0.30 to 0.50 indicate moderate effects, and values exceeding 0.50 represent strong effects.

Subsequently, we assessed the significance of the path coefficients using p-values. Since SmartPLS does not directly provide p-values, we executed a bootstrap routine with 10,000 iterations using the bias-corrected and accelerated bootstrap as the confidence interval method. This approach was chosen based on prior research [75,76]. Additionally, we opted for the one-tailed option as the test type, aligning with our a priori assumptions regarding the signs of path coefficients. This decision reflects our intent to analyze specific and directed effects between latent constructs [77]. The significance level was set at 0.050.

After assessing the path coefficients, the next step involves evaluating the coefficient of determination (R^2) value. Values between 0 and 0.10, 0.11 and 0.30, 0.30 and 0.50, and above 0.50 indicate, respectively, weak, modest, moderate, and strong explanatory power. No specific bounds for R^2 exist; its interpretation depends on the context.

Lastly, predictive power is essential, as R^2 does not assess out-of-sample predictive capability. We used the PLS predict procedure, employing k-fold cross-validation, for this purpose. Shmueli et al. [78] recommend splitting the sample into 10 subgroups (i.e., k = 10) to ensure accuracy. Comparing the root mean squared error results of predictions against the actual observations (PLS-SEM) and the naïve linear regression model provides insights into predictive power. In our case, most indicators display a greater prediction error in root mean squared error than the naïve linear regression model benchmark, indicating low predictive power.

Model Fit

To assess model fit, key metrics include the standardized root mean residual, which ideally should not exceed 0.080 [79], and the normed fit index, which should be above 0.90. In our study, the standardized root mean residual is 0.065, and the normed fit index is 0.684. However, as recommended by Alamer [80], researchers should prioritize establishing the predictive validity of the structural model over theory testing. Therefore, model fit results are highly dependent on the context, and metrics cannot be assessed individual.

Analysis and discussion

Figure *2* illustrates the results of the structural model, including the legend. The constructs, represented by circles, are shown in dark blue if they belong to the UTAUT model and in pale blue if we introduce them. The diagram emphasises the relationships between the latent variables, displaying path coefficients (β) and their significance levels (p-values) in parentheses, with asterisks denoting the significance levels. Thicker arrows indicate significant hypothesis, while R^2 values are indicated within the constructs.

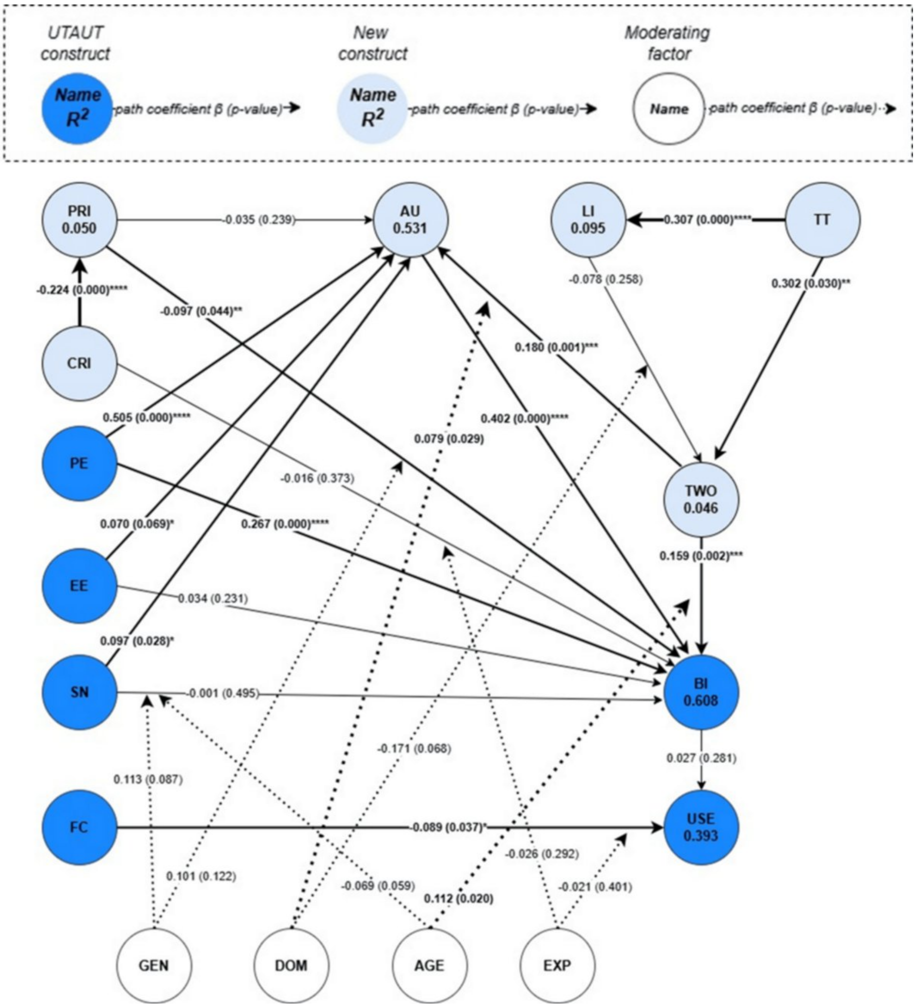

FIGURE 2: Structural model results with verified hypotheses

Findings

To assess the significance and validity of the results, we adhered to the following criteria:

(1) Path coefficient β > 0.20 to demonstrate its significance [81];

(2) P-value should be smaller than 0.05 and T-value should be greater than 1.96 [81];

(3) Cohen's f^2 should be assessed with reference to three different thresholds: ⩾0.02 for a small effect, ⩾0.15 for a medium effect, and ⩾0.35 for a large effect [82].

We will present the findings focusing on the four contexts included in our model: task, individual, technological, and organizational. Table *5* summarizes all the hypotheses, with their significance level, coefficient, and effect size.

The task context aimed to analyze the extent to which the task characteristics influenced the individual context and the BI to use. In this regard, the TT demonstrates a significant positive influence on both constructs' LI ($\beta = 0.304$, $p < 0.001$) and TWO ($\beta = 0.302$, $p < 0.05$). Although small, f^2 confirms that the effect is real in both cases.

Hypotheses		β	p-values	f^2 (effect size)
Direct Effect				
H1a. PE positively impacts the BI to use AI Chatbots		**0.267**	**0.000********	**0.077 (small)**
H1b. PE positively impacts the AU of users		**0.505**	**0.000********	**0.329 (medium)**
H2a. EE positively impacts the BI to use AI Chatbots		0.052	0.137	0.005
H2b. EE positively impacts the AU of users		0.070	0.069*	0.010 (small)
H3a. SN positively impacts the BI to use AI chatbots		0.019	0.367	0.000
H3b. SN positively impacts the AU of users		**0.097**	**0.028***	**0.015 (medium)**
H4. FC positively impact the USE of AI Chatbots		**-0.089**	**0.037***	**0.010 (small)**
H5: The AU has a positive impact on the BI to use AI Chatbots		**0.402**	**0.000********	**0.213 (medium)**
H6a. CRI positively impacts the BI to use AI Chatbots		-0.026	0.294	0.001
H6b. CRI positively impacts the PRI of users		-0.224	0.000****	0.053 (small)
H7a. TWO positively impacts the BI to use AI Chatbots		**0.149**	**0.003******	**0.033 (small)**
H7b. TWO positively impacts the AU of users		**0.180**	**0.001******	**0.045 (small)**
H8a. PRI negatively impacts the BI to use AI Chatbots		**-0.089**	**0.044****	**0.077 (small)**
H8b. PRI negatively impacts the AU of users		-0.035	0.239	0.002
H9a. TT positively impacts the LI among tasks		**0.307**	**0.000********	**0.105 (small)**
H9b. TT positively impacts TWO		**0.302**	**0.049****	**0.020 (small)**
H10. LI positively impacts TWO		-0.100	0.310	0.001
H11. BI positively impacts USE of AI Chatbot		0.027	0.281	0.002
Moderating Effect				
Moderating Effect of AGE	AGE* SN→AU	-0.069	0.059	0.008
	AGE*TWO→BI	**0.112**	**0.020 ****	**0.021 (small)**
Moderating Effect of DOMAIN	**DOM*TWO→AU**	**0.079**	**0.029 ****	**0.085 (small)**
	DOM*LI→TWO	0.171	0.068	0.008
Moderating Effect of EXPERIENCE	EXP*FC→USE	-0.021	0.401	0.000
	EXP*CRI→BI	-0.026	0.292	0.001

TABLE 5: Direct effect and moderating effect (significant effects in bold)

AU, Attitude Towards Innovating; BI, Behavioral Intention; CRI, Critical Thinking; EE, Effort Expectancy; FC, Facilitating Conditions; LI, Level of Interaction; PE, Performance Expectancy; PRI, Perceived Risk; SN, Social Influence; TT, Type of Task; TWO, Team Working; USE, Use Behavior

The effect of LI on TWO is not significant. TWO demonstrates two positive and significant effects on AU ($\beta = 0.180$, $p < 0.001$) and BI ($\beta = 0.159$, $p < 0.05$), both of which are positive. In each case, the p-values, T-values, and f^2 values are consistent with a significant, albeit small, effect.

The individual context aimed to analyze to what extent the personal perceptions and characteristics of the user would influence the user behavior of AI chatbots. Concerning this context, PRI has a small and negative significant impact on the BI constructs ($\beta = -0.097$, $p < 0.05$), indicating that the increased perception of the risk associated with AI chatbots usage reduces the intention to use them.

Similarly, CRI shows a significant, negative, and small effect on PRI ($\beta = -0.224$, $p < 0.001$), in contrast with our hypothesis, showing that increased capability of critically evaluating results produced by AI chatbots reduces the perception of the risk of using them.

The effects of PRI on AU and CRI on BI are not significant, suggesting that the AU is independent of the perception of the risk associated with AI chatbots, and CRI does not influence the decision to adopt AI chatbots. However, the impact of AU is significant, demonstrating a strong relationship and a medium effect ($\beta = 0.402$, $p < 0.000$, $f^2 = 0.213$).

The technological context aimed to analyze the extent to which the performance of AI chatbots and the effort required for their use would impact the intention to use them. In this regard, PE has shown the strongest positive influences, exhibiting a moderate positive relationship with AU, with a medium effect size ($\beta = 0.505$, $p < 0.001$, $f^2 = 0.329$). PE also displays a moderate significant impact on BI, with a small effect size ($\beta = 0.253$, $p < 0.001$, $f^2 = 0.077$).

Finally, the organizational context assessed the influence of context-related social factors and FC on the intention to use. Regarding this aspect, the impact of SN is slightly positive and significant on AU with a small effect size ($\beta = 0.097$, $p < 0.05$, $f^2 = 0.015$). In contrast, the effect on BI is non-significant. Together, these two factors suggest that SN affects the individual context concerning attitudes towards innovation but does not impact the intention to use.

Furthermore, FC displays a negative impact ($\beta = -0.089$, $p < 0.05$) on USE, with a small effect size. The relationship FC→USE also shows a T-value slightly below the threshold of 1.96 ($T_{FC \rightarrow USE} = 1.789$). In this case, since the p-value is significant, the discrepancy can be attributed to a slight difference on how these values are calculated (e.g. bootstrapping method in SmartPLS).

Concerning the moderation factors, results encompass the effect of Domain on TWO→AU ($\beta = 0.079$, $p < 0.05$), which, while somewhat weak, remains significant, and the effect of Age on TWO→BI ($\beta = 0.112$, $p < 0.05$). Other effects appeared to be less significant, demonstrating relatively low moderating effects.

Concerning the R^2, we noticed a relatively low value for the PRI construct, suggesting that CRI accounts for only a small portion of the variance of PRI. The situation is nearly the same for LI (0.095) and TWO (0.046). Conversely, the higher R^2 values observed for AU (0.531) and BI (0.608) indicate stronger predictive power within the model. These results suggest that constructs such as PE, PRI, AU, and TWO collectively contribute to individuals' attitudes towards innovation and subsequent BIs.

Lastly, USE shows a $R^2 = 0.393$, this suggests that approximately 39.3% of the variance in usage behavior in explained by the negative impact of FC and individual's BI.

Discussion

Our analysis reveals mixed results. We can derive several messages and uphold implications for both research and practice.

The first element of discussion pertains to the role of the dimensions of the UTAUT model on the BI to use AI chatbots. In our study, we demonstrate that neither EE nor SN were significant in explaining BI. This contributes to the contradictory situation in the literature, which presents both empirical evidences supporting the UTAUT model and a lack of support for EE and SN, similar to our results [8,57]. Given this inconsistency, further research should explore the significance of the relationship between EE and SN with regard to the BI of using AI chatbots. However, our findings indicate that the PE, EE, and SN constructs of UTAUT significantly explain users' AU, which subsequently influences the intention to use. These results are novel and have not previously been examined in the literature. All coefficients for PE, EE, and SN are positive and demonstrate a medium effect. Notably, the path PE→AU→BI shows a greater effect size in our findings. We interpret these results as follows: the stronger the perception that AI chatbots facilitate knowledge work, the greater the perception of their ease of use, and the more substantial the SN concerning the use of AI chatbots, the stronger the user's AU work with AI chatbots, and consequently, the greater the intention to use.

The second element of discussion concerns the role of CRI and PRI factors and their effects on BI. Also, in this case, the factor CRI shows no direct effect on BI, but a negative indirect effect through PRI since the coefficients are negative in both cases (CRI→PRI and PRI→BI). We read this relationship as follows: the higher the level of CRI of the knowledge worker, the lower the PRI of using AI chatbots. At the same time, the higher the PRI of using AI chatbots, the lower the intention to use them. The literature contains already evidence from quantitative studies [83] and qualitative studies to confirm that the PRI of AI chatbots can reduce the intention to use. Furthermore, the concern on the literature is on the artefact and its limit of not always providing correct answers. Given the negative relationship between CRI and PRI, and PRI and BI, our results indicate that knowledge workers with high levels of CRI may have a heightened intent to use, even if the output of the AI may remain somewhat untrustworthy. Hence, higher levels of

CRI can revert the negative path of PRI on BI, which is a path currently not considered by the literature. However, since the effect is small, further research should investigate the absence of a connection between CRI and intention to use, as we anticipated, and avoid relying on self-reported measures for assessing CRI.

An additional point of discussion concerns the exploration of the nature of the task. Our results demonstrate that TT influences LI and TWO, while TWO affects BI and AU. Although all these effects are supported, they remain relatively small. With regard to these constructs, we investigated various paths but identified no effects beyond those we are reporting. The results suggest that, regardless of whether the nature of the task involves the types of interactions developed among knowledge workers, only teamwork significantly influences the intention to use and acts as an antecedent for AU.

The influence of teamwork on attitudes towards innovating is substantiated by clear evidence in the innovation literature [84], particularly concerning knowledge workers using AI chatbots. Our findings also suggest that the domain moderates this relationship, indicating that team dynamics in different contexts may impact perceived innovation in various manners. In our model, the domain (DOM) is measured categorically to reflect the diverse areas from which data was gathered. Based on the value of this variable, we can assert that in highly bureaucratic domains, such as the Italian judiciary system (DOM = 1), rigid adherence to formal norms may restrict the extent to which team collaboration encourages openness to innovation. Conversely, the moderating effect is less restrictive in fields such as Public Education and Management (DOM = 2), which offer a more balanced approach between norm adherence and creativity, while still maintaining some level of bureaucratic culture. The most significant moderating effect is observed in the Digital Content Production and Web Design sector (DOM = 3), where creativity and innovation are paramount, and normative constraints are minimal. This variation across domains highlights how sector-specific cultural norms and practices can influence the extent to which TWO fosters openness to innovation and the intention to pursue it.

Age also emerged as a moderating factor (AGE*TWO→BI) in the relationship between teamwork and BI. Our results indicate that the impact of teamwork on BI is more pronounced among younger participants who, as digital natives, are likely more adept at using innovative digital tools such as AI chatbots [85].

In our results, the relationship between BI and actual usage is not supported. While this finding contradicts the validated UTAUT model, we attribute it to a confounding factor in our data collection setting, where respondents were required to use the chatbot. Since the training session was part of their work, participants may have viewed their use of the chatbot as mandatory rather than voluntary. Instead, we want to emphasize that FC negatively affect actual usage, possessing moderate explanatory power, which suggests a potential alternative explanation: the organizational context may inhibit knowledge workers from engaging in actual usage. Future research should directly examine the role of organizational and institutional contexts on both the intention to use and the actual use of AI chatbots, also exploring whether this may have a negative feedback effect on the antecedents of intention to use, especially AU.

A final comment addresses the effect size of the hypotheses, which is small for most of them. As indicated by the literature, such results are anticipated with PLS analysis when working with latent variables, and remain meaningful in the presence of adequate R^2, particularly when studying complex phenomena [86,87].

Theoretical implications

Our results add to the contradicting observations on the validity of UTAUT constructs to explain AI chatbot usage available in the literature [16,57], raising theoretical implications.

The first implication concerns the role of AU in the UTAUT model as a validated antecedent of BI, influenced by EE, PE, and SN. This relationship may connect with the use of a recent innovation (AI chatbot), where the user's attitude towards the innovation drives their intention to use it. These findings suggest that the relationships among the UTAUT constructs are more complex than initially thought. Future research should investigate these relationships beyond knowledge work and explore the underlying mechanisms, which, if validated, could improve our theoretical understanding of AI chatbot usage intentions.

A second theoretical implication relates to the role of CRI and PRI in the intention to use AI chatbots. The path CRI→PRI→BI exhibits negative coefficients and moderate explanatory power for PRI. This pathway has not been previously tested in the literature and could serve as a reconciliation strategy to address concerns about the risks associated with AI chatbot usage [3,20,21]. Further research should focus on testing the validity of this path across different samples, including those outside the domain of knowledge workers.

Expanding on this aspect, given that AI applications may pose significant risks, another implication is to theoretically unpack the concept of risk. This involves breaking it down into specific risks, such as biases, misinformation, or inaccurate information, to better understand the impact on the intention to use and to test whether the effect of CRI applies uniformly across all risks. Lastly, concerning CRI, our work also suggests a methodological implication. Since self-reported measures may overestimate CRI [88], future research should integrate objective measures of CRI into research models, utilizing experimental or quasi-experimental designs.

Considering the lack of significance of the task characteristics for the intention to use in our results, a theoretical implication for future research would be to use a different theoretical approach to test whether the task characteristics influence the intention to use or not, either by developing new constructs or by leveraging validated constructs such as task technology fit theory.

Finally, considering the negative impact of FC on actual use and the relevance of the domain in at least one path in our model, we suggest future research to explore the impact of the organizational and institutional environment, which may constitute a barrier to using AI chatbots.

Practical implications

Our findings offer some practical insights for organizations and knowledge workers.

PE significantly influences BI, illustrating a pathway to boost AI chatbot adoption. Organizations should prioritize showcasing the tangible benefits of AI chatbots in task facilitation, especially regarding efficiency and innovation. When knowledge workers perceive these tools as beneficial, they are more likely to adopt a positive attitude towards AI innovation, increasing their willingness to embrace these technologies.

A second implication relates to PRI and CRI. While PRI may deter organizations from using AI chatbots, CRI can help mitigate the risks of untrustworthy results. Organizations should implement comprehensive risk communication strategies addressing functional risks, like cybersecurity vulnerabilities, and emotional concerns. Additionally, both organizations and knowledge workers should adopt a critical perspective toward AI chatbots.

Our findings show that the work environment affects the factors influencing AI chatbot adoption, especially regarding TW, AU, and BI, and the institutional context's impact on AU, USE, BI, and USE. Organizations need to recognize that specific contexts, such as a bureaucratic culture in the judicial domain, may limit knowledge workers' ability to experiment with AI chatbots. Promoting a collaborative innovation approach may facilitate AI adoption. Furthermore, the role of AGE in the relationship between TW and BI highlights the necessity for age-sensitive strategies when encouraging AI chatbot adoption, particularly for older employees who may resist exploring AI innovations.

Lastly, organizations considering AI chatbots should first assess internal dynamics, as knowledge workers with AU might already be experimenting but may not utilize AI chatbots due to organizational constraints.

Conclusions

In this paper, we aimed to contribute to the literature exploring the adoption of AI chatbots by extending the UTAUT with new constructs and hypotheses. Following RQ1, our results indicate that the UTAUT factors impact BI differently than in the validated model. In particular, only PE shows a supported impact on BI, while PE, EE, and SN positively influence AU, which serves as a new antecedent to BI. These findings support and extend similar evidence in the literature. However, further research is necessary to explore the role of AU in relation to the intention of knowledge workers to use AI chatbots. Regarding RQ2, the individual context has a more substantial effect on the intention to use, particularly through two paths, both novel for the literature: PE→AU→BI and CRI→PRI→BI. In contrast, the organizational context exhibits a negative impact on USE with moderate explanatory power, while the task context requires further exploration since only TWO dynamics affect AU and BI. Further research should investigate these aspects, addressing the various risk factors of AI chatbots or employing different theoretical frameworks for the task dimension, or seeking greater diversity in the types of task being analyzed.

We must acknowledge two limitations of this research. First, our data collection represents a cross-sectional multi-sector observation. With this strategy, strategy compensates for the limitations of a purely cross-sectional analysis; however, we are still addressing only a few domains. We refrain from generalizing our results beyond the mid-range created by knowledge workers and the domains we examined, and further research would be necessary to investigate the identified relationships in different domains more deeply. A second limitation stems from the characteristics of the sample used in this study. Data collection took place in the context of seminars on AI and chatbot usage designed specifically for knowledge workers. This might introduce a potential bias, as participants may have higher expectations regarding chatbot performance and perceive lower levels of risk. Future research could address a more diverse sample of knowledge workers.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Filippo Bianchini, Francesca De Luzi, Mattia Macrì, Alessio M. Braccini, Massimo Mecella

Acquisition, analysis, or interpretation of data: Filippo Bianchini, Francesca De Luzi, Mattia Macrì, Alessio M. Braccini

Drafting of the manuscript: Filippo Bianchini, Francesca De Luzi, Mattia Macrì, Alessio M. Braccini

Critical review of the manuscript for important intellectual content: Filippo Bianchini, Francesca De Luzi, Alessio M. Braccini, Massimo Mecella

Supervision: Filippo Bianchini, Francesca De Luzi, Mattia Macrì, Alessio M. Braccini, Massimo Mecella

Disclosures

Human subjects: Consent was obtained or waived by all participants in this study. Not applicable issued approval Not applicable. This study involved anonymous survey data and did not involve patients or clinical interventions. According to the policies of the University of Rome Sapienza and University of Tuscia, formal ethics committee approval was not required. All participants provided written informed consent prior to participation. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Acknowledgements

Data and study materials are available on reasonable request from Bianchini (bianchini@diag.uniroma1.it). The work of Filippo Bianchini and Massimo Mecella is partially funded by MICS (Made in Italy—Circular and Sustainable) (PE00000004) Extended Partnership (CUP B53C22004130001) funded by the EU - NextGenerationEU PNRR MUR. The work of Mattia Macrì has been supported by the PhD fellowship Pubblica Amministrazione DM118 - CUP B83C22003460006.

References

1. Balakrishnan J, Dwivedi YK: Role of cognitive absorption in building user trust and experience. Psychology and Marketing. 2021, 38:643-668. 10.1002/mar.21462
2. Chandra S, Shirish A, Srivastava SC: To be or not to be ...human? Theorizing the role of human-like competencies in conversational artificial intelligence agents. Journal of Management Information Systems. 2022, 39:969-1005. 10.1080/07421222.2022.2127441
3. Gregor S: Responsible artificial intelligence and journal publishing. Journal of the Association for Information Systems. 2024, 25:48-60. 10.17705/1jais.00863
4. Al-Natour S, Benbasat I, Cenfetelli R: Designing online virtual advisors to encourage customer self-disclosure: A theoretical model and an empirical test. Journal of Management Information Systems. 2021, 38:798-827. 10.1080/07421222.2021.1962595
5. Cui R, Li M, Zhang S: AI and procurement. Manufacturing & Service Operations Management. 2022, 24:691-706. 10.1287/msom.2021.0989
6. Balakrishnan J, Abed SS, Jones P: The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services?. Technological Forecasting and Social Change. 2022, 180:121692. 10.1016/j.techfore.2022.121692
7. Meyer-Waarden L, Pavone G, Poocharoentou T, Prayatsup P, Ratinaud M, Tison A, Torné S: How service quality influences customer acceptance and usage of chatbots?. Journal of Service Management Research. 2020, 4:35-51. 10.15358/2511-8676-2020-1-35
8. Camilleri MA: Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework. Technological Forecasting and Social Change. 2024, 201:123247. 10.1016/j.techfore.2024.123247
9. Han E, Yin D, Zhang H: Bots with feelings: Should AI agents express positive emotion in customer service?. Information Systems Research. 2023, 34:1296-1311. 10.1287/isre.2022.1179

10. Zhang J, Wang X, Lu J, Liu L, Feng Y: The impact of emotional expression by artificial intelligence recommendation chatbots on perceived humanness and social interactivity. Decision Support Systems. 2024, 187:114347. 10.1016/j.dss.2024.114347
11. Baird A, Maruping LM: The next generation of research on IS use: A theoretical framework of delegation to and from agentic IS artifacts. MIS Quarterly. 2021, 45:315-341. 10.25300/misq/2021/15882
12. Chatterjee S, Rana NP, Khorana S, Mikalef P, Sharma A: Assessing organizational users' intentions and behavior to AI integrated CRM systems: A meta-UTAUT approach. Information Systems Frontiers. 2023, 25:1299-1313. 10.1007/s10796-021-10181-1
13. Saffarizadeh K, Keil M, Boodraj M, Alashoor T: "My Name is Alexa. What's Your Name?" The impact of reciprocal self-disclosure on post-interaction trust in conversational agents. Journal of the Association for Information Systems. 2024, 25:528-568. 10.17705/1jais.00839
14. Handa K, Tamkin A, McCain M, et al.: Which economic tasks are performed with AI? Evidence from millions of Claude conversations. arXiv. 2025, 10.48550/arXiv.2503.04761
15. Sachdeva A, Kim A, Dennis AR: Taking the chat out of chatbot? Collecting user reviews with chatbots and web forms. Journal of Management Information Systems. 2024, 41:146-177. 10.1080/07421222.2023.2301175
16. Sarraf S, Kar AK, Janssen M: How do system and user characteristics, along with anthropomorphism, impact cognitive absorption of chatbots - Introducing SUCCAST through a mixed methods study. Decision Support Systems. 2024, 178:114132. 10.1016/j.dss.2023.114132
17. Bianchini F, Braccini AM, De Luzi F, Macrì M, Mecella M, Ruggiero R: Factors driving chatbot adoption in the legal domain: a fuzzy-set qualitative comparative analysis in the Italian domain. ECIS 2025 Proceedings. 2025, 10:1-16.
18. Bianchini F, Calamo M, De Luzi F, Macrì M, Mecella M: Enhancing complex linguistic tasks resolution through fine-tuning LLMs, RAG and knowledge graphs (short paper). Advanced Information Systems Engineering Workshops. Almeida JPA, Di Ciccio C, Kalloniatis C (ed): Springer, Cham; 2024. 521:147-155. 10.1007/978-3-031-61003-5_13
19. Bianchini F, Calamo M, De Luzi F, Macrì M, Mecella M: A service-based pipeline for complex linguistic tasks adopting LLMs and knowledge graphs. Service-Oriented Computing. Aiello M, Barzen J, Dustdar S, Leymann F (ed): Springer, Cham; 2024. 2221:145-161. 10.1007/978-3-031-72578-4_8
20. Ngwenyama O, Rowe F: Should we collaborate with AI to conduct literature reviews? Changing epistemic values in a flattening world. Journal of the Association for Information Systems. 2024, 25:122-136. 10.17705/1jais.00869
21. Susarla A, Gopal R, Thatcher JB, Sarker S: The Janus effect of generative AI: Charting the path for responsible conduct of scholarly activities in information systems. Information Systems Research. 2023, 34:399-408. 10.1287/isre.2023.ed.v34.n2
22. Surawski B: Who is a "knowledge worker" - clarifying the meaning of the term through comparison with synonymous and associated terms. Management. 2019, 23:105-133. 10.2478/manment-2019-0007
23. Sowa K, Przegalinska A, Ciechanowski L: Cobots in knowledge work Human - AI collaboration in managerial professions. Journal of Business Research. 2021, 125:135-142. 10.1016/j.jbusres.2020.11.038
24. Kankanhalli A: Peer review in the age of generative AI. Journal of the Association for Information Systems. 2024, 25:76-84. 10.17705/1jais.00865
25. Abdul-Kader SA, Woods J: Survey on chatbot design techniques in speech conversation systems. International Journal of Advanced Computer Science and Applications. 2015, 6:72-80. 10.14569/ijacsa.2015.060712
26. Chowdhary KR: Fundamentals of Artificial Intelligence. Springer, New Delhi; 2020. 10.1007/978-81-322-3972-7
27. Nuruzzaman M, Hussain OK: A survey on chatbot implementation in customer service industry through deep neural networks. 2018 IEEE 15th International Conference on e-Business Engineering (ICEBE), Xi'an, China. 2018, 54-61. 10.1109/ICEBE.2018.00019
28. Zhao H, Min Q: Exploring continued usage of an AI teaching assistant among university students: A temporal distance perspective. Information & Management. 2024, 61:104012. 10.1016/j.im.2024.104012
29. Bai Y, Kadavath S, Kundu S, et al.: Constitutional AI: Harmlessness from AI feedback. arXiv. 2022, 10.48550/arXiv.2212.08073
30. Touvron H, Lavril T, Izacard G, et al.: LLaMA: open and efficient foundation language models. 2023, 10.48550/arXiv.2302.13971
31. Chowdhery A, Narang S, Devlin J, et al.: PaLM: scaling language modeling with Pathway. arXiv. 2022, 10.48550/arXiv.2204.02311
32. Tay Y, Wei J, Chung HW, et al.: Transcending scaling laws with 0.1% extra compute. arXiv. 2022, 10.48550/arXiv.2210.11399
33. Mirbabaie M, Brendel AB, Hofeditz L: Ethics and AI in information systems research. Communications of the Association for Information Systems. 2022, 50:726-753. 10.17705/1cais.05034
34. Araujo T: Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. Computers in Human Behavior. 2018, 85:183-189. 10.1016/j.chb.2018.03.051
35. Mirbabaie M, Stieglitz S, Brünker F, Hofeditz L, Ross B, Frick NRJ: Understanding collaboration with virtual assistants - The role of social identity and the extended self. Business & Information Systems Engineering. 2021, 63:21-37. 10.1007/s12599-020-00672-x
36. Seeber I, Bittner E, Briggs RO, et al.: Machines as teammates: A research agenda on AI in team collaboration. Information & Management. 2020, 57:103174. 10.1016/j.im.2019.103174
37. Boddington P: Does AI raise any distinctive ethical questions?. Towards a Code of Ethics for Artificial Intelligence. Artificial Intelligence: Foundations, Theory, and Algorithms. Springer, Cham; 10.1007/978-3-319-60648-4_3. 27-37. 10.1007/978-3-319-60648-4_3
38. Vassilakopoulou P, Haug A, Salvesen LM, Pappas IO: Developing human/AI interactions for chat-based customer services: lessons learned from the Norwegian government. European Journal of Information Systems. 2022, 32:10-22. 10.1080/0960085x.2022.2096490
39. Gnewuch U, Morana S, Hinz O, Kellner R, Maedche A: More than a bot? The impact of disclosing human involvement on customer interactions with hybrid service agents. Information Systems Research. 2024, 35:936-

955. 10.1287/isre.2022.0152

40. Schanke S, Burtch G, Ray G: Estimating the impact of “humanizing” customer service chatbots. Information Systems Research. 2021, 32:736-751. 10.1287/isre.2021.1015
41. Grimes GM, Schuetzler RM, Giboney JS: Mental models and expectation violations in conversational AI interactions. Decision Support Systems. 2021, 144:113515. 10.1016/j.dss.2021.113515
42. Meier M, Maier C, Thatcher JB, Weitzel T: Chatbot interactions: How consumption values and disruptive situations influence customers' willingness to interact. Information Systems Journal. 2024, 34:1579-1625. 10.1111/isj.12507
43. Montenegro-Rueda M, Fernández-Cerero J, Fernández-Batanero JM, López-Meneses E: Impact of the implementation of ChatGPT in education: A systematic review. Computers. 2023, 12:153. 10.3390/computers12080153
44. Lo CK: What is the impact of ChatGPT on education? A rapid review of the literature. Education Sciences. 2023, 13:410. 10.3390/educsci13040410
45. Budhathoki T, Zirar A, Njoya ET, Timsina A: ChatGPT adoption and anxiety: a cross-country analysis utilising the unified theory of acceptance and use of technology (UTAUT). Studies in Higher Education. 2024, 49:831-846. 10.1080/03075079.2024.2333937
46. Awal MR, Haque ME: Revisiting university students' intention to accept AI-Powered chatbot with an integration between TAM and SCT: a south Asian perspective. Journal of Applied Research in Higher Education. 2024, 17:594-608. 10.1108/jarhe-11-2023-0514
47. Bhat MA, Tiwari CK, Bhaskar P, Khan ST: Examining ChatGPT adoption among educators in higher educational institutions using extended UTAUT model. Journal of Information Communication and Ethics in Society. 2024, 22:331-353. 10.1108/jices-03-2024-0033
48. Elkhatibi Y, Guelzim H, Benebdelouahed R: Factors influencing the adoption of AI-powered chatbots in the Moroccan banking sector: An extended UTAUT model. Journal of Logistics Informatics and Service Science. 2024, 11:559-585. 10.33168/jliss.2024.0730
49. Venkatesh V, Morris MG, Davis GB, Davis FD: User acceptance of information technology: Toward a unified view. MIS Quarterly. 2003, 27:425-478. 10.2307/30036540
50. Williams MD, Rana NP, Dwivedi YK: The unified theory of acceptance and use of technology (UTAUT): a literature review. Journal of Enterprise Information Management. 2015, 28:443-488. 10.1108/jeim-09-2014-0088
51. Silva P: Davis' technology acceptance model (TAM). Information Seeking Behavior and Technology Adoption: Theories and Trends. Al-Suqri M, Al-Aufi A (ed): IGI Global Scientific Publishing, Pennsylvania; 1989. 205-219. 10.4018/978-1-4666-8156-9.ch013
52. Valtolina S, Matamoros RA, Musiu E, Epifania F, Villa M: Extended UTAUT model to analyze the acceptance of virtual assistant’s recommendations using interactive visualisations. AVI '22: Proceedings of the 2022 International Conference on Advanced Visual Interfaces. 2022, 1-5. 10.1145/3531073.3531129
53. Wang YY, Luse A, Townsend AM, Mennecke BE: Understanding the moderating roles of types of recommender systems and products on customer behavioral intention to use recommender systems. Information Systems and e-Business Management. 2014, 13:769-799. 10.1007/s10257-014-0269-9
54. Raffaghelli JE, Rodríguez ME, Guerrero-Roldán AE, Bañeres D: Applying the UTAUT model to explain the students' acceptance of an early warning system in higher education. Computers & Education. 2022, 182:104468. 10.1016/j.compedu.2022.104468
55. Saari UA, Tossavainen A, Kaipainen K, Mäkinen SJ: Exploring factors influencing the acceptance of social robots among early adopters and mass market representatives. Robotics and Autonomous Systems. 2022, 151:104033. 10.1016/j.robot.2022.104033
56. Šumak B, Šorgo A: The acceptance and use of interactive whiteboards among teachers: Differences in UTAUT determinants between pre- and post-adopters. Computers in Human Behavior. 2016, 64:602-620. 10.1016/j.chb.2016.07.037
57. Huy LV, Nguyen HTT, Vo-Thanh T, Thinh NHT, Dung TTT: Generative AI, why, how, and outcomes: A user adoption study. AIS Transactions on Human-Computer Interaction. 2024, 16:1-27. 10.17705/1thci.00198
58. Vargas Murillo AR, de la Asuncion Pari Bedoya INM, Guevara-Soto FJ: Challenges and opportunities of AI-assisted learning: A systematic literature review on the impact of ChatGPT usage in higher education. International Journal of Learning Teaching and Educational Research. 2023, 22:122-135. 10.26803/ijlter.22.7.7
59. Xu Z, Jain S, Kankanhalli M: Hallucination is inevitable: An innate limitation of large language models. arXiv. 2025, 10.48550/arXiv.2401.11817
60. Bingham CB, Howell T, Ott TE: Capability creation: Heuristics as microfoundations. Strategic Entrepreneurship Journal. 2019, 13:121-153. 10.1002/sej.1312
61. John SP, De’Villiers R: Elaboration of marketing communication through visual media: An empirical analysis. Journal of Retailing and Consumer Services. 2020, 54:102052. 10.1016/j.jretconser.2020.102052
62. Winter S: Do anticipated Facebook discussions diminish the importance of argument quality? An experimental investigation of attitude formation in social media. Media Psychology. 2019, 23:79-106. 10.1080/15213269.2019.1572521
63. Ajzen I: The theory of planned behavior. Organizational Behavior and Human Decision Processes. 1991, 50:179-211. 10.1016/0749-5978(91)90020-t
64. Young AT, Amara D, Bhattacharya A, Wei ML: Patient and general public attitudes towards clinical artificial intelligence: a mixed methods systematic review. The Lancet Digital Health. 2021, 3:e599-e611. 10.1016/s2589-7500(21)00132-1
65. Skov SS, Andersen JR, Lauridsen S, Bab M, Bundsbæk M, Nielsen MBD: Designing a conversational agent to promote teamwork and collaborative practices using design thinking: An explorative study on user experiences. Frontiers in Psychology. 2022, 13:903715. 10.3389/fpsyg.2022.903715
66. Lee JH, Song CH: Effects of trust and perceived risk on user acceptance of a new technology service. Social Behavior and Personality: An International Journal. 2013, 41:587-597. 10.2224/sbp.2013.41.4.587
67. Perrow C: A framework for the comparative analysis of organizations. American Sociological Review. 1967, 32:194. 10.2307/2091811
68. Thompson JD: Organizations in Action: Social Science Bases of Administrative Theory. Routledge, New York;

2017. 10.4324/9781315125930
69. Melián-González S, Gutiérrez-Taño D, Bulchand-Gidumal J: Predicting the intentions to use chatbots for travel and tourism. Current Issues in Tourism. 2019, 24:192-210. 10.1080/13683500.2019.1706457
70. Gursoy D, Chi OH, Lu L, Nunkoo R: Consumers acceptance of artificially intelligent (AI) device use in service delivery. International Journal of Information Management. 2019, 49:157-169. 10.1016/j.ijinfomgt.2019.03.008
71. Lin H, Chi OH, Gursoy D: Antecedents of customers' acceptance of artificially intelligent robotic device use in hospitality services. Journal of Hospitality Marketing & Management. 2019, 29:530-549. 10.1080/19368623.2020.1685053
72. Hair J, Alamer A: Partial least squares structural equation modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. Research Methods in Applied Linguistics. 2022, 1:100027. 10.1016/j.rmal.2022.100027
73. Hair JF, Risher JJ, Sarstedt M, Ringle CM: When to use and how to report the results of PLS-SEM. European Business Review. 2019, 31:2-24. 10.1108/ebr-11-2018-0203
74. Diamantopoulos A, Siguaw JA: Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. British Journal of Management. 2006, 17:263-282. 10.1111/j.1467-8551.2006.00500.x
75. MacKinnon DP, Lockwood CM, Williams J: Confidence limits for the indirect effect: Distribution of the product and resampling methods. Multivariate Behavioral Research. 2004, 39:99-128. 10.1207/s15327906mbr3901_4
76. Williams J, MacKinnon DP: Resampling and distribution of the product methods for testing indirect effects in complex models. Structural Equation Modeling A Multidisciplinary Journal. 2008, 15:23-51. 10.1080/10705510701758166
77. Kock N: One-tailed or two-tailed p values in PLS-SEM?. International Journal of e-Collaboration. 2015, 11:1-7. 10.4018/ijec.2015040101
78. Shmueli G, Sarstedt M, Hair JF, Cheah JH, Ting H, Vaithilingam S, Ringle CM: Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. European Journal of Marketing. 2019, 53:2322-2347. 10.1108/ejm-02-2019-0189
79. Hu L, Bentler PM: Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. Psychological Methods. 1998, 3:424-453. 10.1037/1082-989x.3.4.424
80. Alamer A: Having a single language interest autonomously predicts L2 achievement: Addressing the predictive validity of L2 grit. System. 2022, 108:102850. 10.1016/j.system.2022.102850
81. Wong KKK: Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. Marketing Bulletin. 2013, 24:1-32. 10.1007/978-3-319-05542-8_15-2
82. Cohen J: Statistical power analysis. Current Directions in Psychological Science. 1992, 1:98-101. 10.1111/1467-8721.ep10768783
83. Li W: A study on factors influencing designers' behavioral intention in using AI-generated content for assisted design: Perceived anxiety, perceived risk, and UTAUT. International Journal of Human-Computer Interaction. 2024, 41:1064-1077. 10.1080/10447318.2024.2310354
84. Fay D, Shipton H, West MA, Patterson M: Teamwork and organizational innovation: The moderating role of the HRM context. Creativity and Innovation Management. 2014, 24:261-277. 10.1111/caim.12100
85. Braccini AM, Federici T: A measurement model for investigating digital natives and their organisational behaviour. International Conference on Information Systems (ICIS). 2013, 72:1-10.
86. Henseler J, Ringle CM, Sinkovics RR: The use of partial least squares path modeling in international marketing. New Challenges to International Marketing. Sinkovics RR, Ghauri PN (ed): Emerald, Bingley; 2009. 20:277-319. 10.1108/S1474-7979(2009)0000020014
87. Hair JF, Ringle CM, Sarstedt M: PLS-SEM: Indeed a silver bullet. The Journal of Marketing Theory and Practice. 2011, 19:139-152. 10.2753/mtp1069-6679190202
88. Abrami PC, Bernard RM, Borokhovski E, Waddington DI, Wade CA, Persson T: Strategies for teaching students to think critically: A meta-analysis. Review of Educational Research. 2015, 85:275-314. 10.3102/0034654314551063