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DOI
10.1080/0144929X.2024.2317364

Publication date
2024

Document Version
Final published version

Published in
Behaviour and Information Technology

Behaviour & Information Technology

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tbit20

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BEHAVIOUR & INFORMATION TECHNOLOGY
https://doi.org/10.1080/0144929X.2024.2317364

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Understanding students' adoption of the ChatGPT chatbot in higher education: the role of anthropomorphism, trust, design novelty and institutional policy

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ABSTRACT
The present research aims to highlight the underlying factors that drive students' adoption of the ChatGPT chatbot in higher education. This study extends the meta-UTAUT framework by including additional exogenous factors of anthropomorphism, trust, design novelty, and institutional policy. Empirical examination with Structural Equation Modelling among 355 students in Dutch higher education institutions revealed attitude and behavioural intention as significant positive predictors of students' ChatGPT use behaviour. Institutional policy negatively moderated the effect of behavioural intention on use behaviour. Behavioural intention was significantly and positively influenced by attitude, performance expectancy, social influence, and facilitating conditions. Anthropomorphism, design novelty, trust, performance expectancy, and effort expectancy were unveiled as significant positive antecedents of attitude. The central theoretical contributions of this research include investigating students' use behaviour instead of behavioural intention, establishing attitude as a core construct, underlining additional antecedents of attitude, and highlighting the importance of institutional policy. The present study contributes to prior research on technology adoption, especially in the area of artificial intelligence in education. The findings yield valuable insights for chatbot designers, product managers, and higher education policy writers.

ARTICLE HISTORY
Received 29 August 2023
Accepted 2 February 2024

KEYWORDS
Anthropomorphism; chatbot adoption; ChatGPT; design novelty; higher education; meta-UTAUT

1. Introduction

The emergence of novel artificial intelligence (AI) technologies has significantly influenced individuals, organisations, and societies in various domains (Dwivedi et al. 2023; Makridakis 2017). The context of higher education is not an exception (Rudolph, Tan, and Tan 2023). One of the most popular AI technologies used to support teaching and learning activities is the Chatbot system (Zhou et al. 2023). A chatbot is a computer program that conducts a conversation in a natural language and sends a response based on business rules and data tuned by the organisation (Balakrishnan and Dwivedi 2021a). The growth of chatbots has drawn the attention of both academia and industry (Haenlein and Kaplan 2021), due to their offering of potentially novel opportunities in the fields of communication (Zhou et al. 2023), customer experience (Luo et al. 2019) and purchase intention (Sindhu and Bharti 2024; Yen and Chiang 2021), user satisfaction (Rapp, Curti, and Boldi 2021), social interactions (Pentina, Hancock, and Xie 2023; Skjuve et al. 2022), healthcare (Kiuchi, Otsu, and Hayashi 2023; Valtolina, Barricelli, and Di Gaetano 2020) and, importantly, educational transformations (Andersen, Mørch, and Litherland 2022; Dwivedi et al. 2023; Wang et al. 2023). Research has demonstrated that chatbots can facilitate learning within higher education (Clarizia et al. 2018) by developing insights into learners' behaviour and improving their learning outcomes (Kuhail et al. 2023), providing students with course contents (Cunningham-Nelson et al. 2019), advice (Ismail and Ade-Ibijola 2019), campus path direction (Mabunda and Ade-Ibijola 2019), active learning and cognitive engagement (Hobert, Følstad, and Law 2023) and promotion of engineering design behaviour (Chien and Yao 2022), thus shaping the student experience (Okonkwo and Ade-Ibijola 2021).

Even though AI chatbots initially originated six decades ago with computer programs like ELIZA

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(Weizenbaum 1966), the emergence of more novel chatbots is prevalent. A new AI chatbot, ChatGPT, was launched by a company, OpenAI, in November 2022 as a follow-up to the GPT-3 family of language models (OpenAI 2022). ChatGPT is an advanced language model based on reinforcement learning that can generate human-like text and engage in sophisticated conversations with users, with the potential to transform the way we learn, teach, and access information (Dwivedi et al. 2023). ChatGPT can provide highly personalised and interactive support to students, including answering complex queries, providing feedback on assignments, and facilitating open-ended discussions about learning experiences. This versatility positions ChatGPT distinctively alongside other chatbot technologies deployed in universities for tailored functionalities (Gill et al. 2024; Pérez, Daradoumis, and Puig 2020). For instance, Lola, Dina and, Whatsapp chatbots used in higher education institutions in Europe and Asia are specifically built to manage enrollment-related queries, while Autotutor, CourseQ, CEUBot, and LTKABot have their designed functionalities in providing support for related courses and encouraging learning through conversation (Pérez, Daradoumis, and Puig 2020). Thus, while the preexistent educational chatbots are typically categorised into service-oriented, teaching-oriented, feedback, language-learning, and motivation types based on their functionalities (Wollny et al. 2021), ChatGPT transcends these categories, offering a comprehensive range of services from interactive language learning and personalised feedback to motivational support, within its advanced natural language processing capabilities.

Due to the ChatGPT's unprecedented features and its potential to challenge the status quo of the learning environments in higher education, recent academic research has converged to an *exploratory approach* on how ChatGPT has initiated a new era in higher education. For instance, ChatGPT can be leveraged to maximise teaching and learning through the promotion of personalised and interactive learning experiences (Dwivedi et al. 2023), or through generating prompts for formative assessment activities that provide ongoing feedback (Baidoo-Anu and Ansah 2023).

However, there is, so far, a *scarcity* of studies which empirically investigate the factors driving students' use behaviour of ChatGPT within the higher education setting. While recent studies (Bonsu and Baffour-Koduah 2023; Menon and Shilpa 2023) have explored the students' perceptions and intentions towards ChatGPT using qualitative or mixed-methods approaches, and others (Jo 2023; Strzelecki 2023) have examined the influence of habit, performance expectancy, hedonic motivation, personal innovativeness and utilitarian benefits on students' behavioural intentions and use behaviour, further empirical research is essential for two reasons: first, we need to shed light on the factors that predict students' adoption of ChatGPT, by also taking the chatbot characteristics, as well as the institutional implementation of policies that promote or control its use (Dwivedi et al. 2023; Lo 2023) into consideration. Regarding the latter, there is scarce evidence on the dynamics of institutional policy implementation for ChatGPT across different educational settings, such as higher education, highlighting the need for further research in the field. Second, the emergence of responsible principles in chatbot development and use (Polyportis and Pahos 2024; Weiss et al. 2023) underscores the significance of underexplored yet vital individual difference core constructs, such as attitude (Dwivedi et al. 2019), as antecedents of students' adoption of ChatGPT in higher education. Consequently, further empirical research highlighting additional endogenous mechanisms that shape students' use behaviour is crucial as it can help educators adapt their methods to groups of students who may be more or less prone to adopt this disruptive technology.

Prior studies on the adoption of chatbots have typically considered such adoption from a user perspective, with minimal consideration of how exogenous factors and attitudes can influence such adoption (Balakrishnan, Abed, and Jones 2022). Considering that state-of-the-art scientific knowledge has reported a shift in technology acceptance from a quiver of diverse theoretical frameworks to the meta-UTAUT framework, in the present study, we adopt the premises of Dwivedi et al. (2019). Thus, it is essential to validate the meta-UTAUT framework since it has not been empirically examined for the acceptance and use of emerging chatbots such as ChatGPT in higher education. From this perspective, this study is, to our knowledge, the first one that has included additional factors along with the key constructs of the meta-UTAUT model to explain students' adoption of ChatGPT in higher education.

The present study contributes to prior research on technology adoption, especially in the area of AI in education, and yields both theoretical and practical implications. First, we unveil the antecedents of students' use of chatbots, such as ChatGPT, in higher education during their early adoption phase. Towards this direction, we consider user factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions (Dwivedi et al. 2019; Venkatesh et al. 2003). At the same time, we incorporate the additional exogenous factors of anthropomorphism (Balakrishnan and Dwivedi 2021b; Balakrishnan, Abed, and Jones 2022), trust (Patil et al. 2020; Yen and Chiang 2021), and design novelty (Mugge and Dahl 2013), to understand their effect on attitude. Second, Dwivedi et al. (2019) corroborated the importance of investigating attitude as a core construct of UTAUT, which is also the focus of the present study. Third, we investigate students' use behaviour instead of behavioural intention, which has been overlooked in prior adoption research (Patil et al. 2020). Fourth, introducing institutional policy as a moderating factor in the framework can provide novel insights into how higher education managers and policy writers can exert a significant influence on students' use behaviour.

The following research questions derive from the discussion and the above objectives. Research questions:

RQ1: Which factors drive students' attitude, behavioural intention to adopt and use behaviour of ChatGPT in higher education?

RQ2: How does institutional policy affect the relationship between behavioural intention and use behaviour of ChatGPT in higher education?

The rest of the paper is structured in the following way: we proceed with the theoretical background, then with the development of a set of testable hypotheses, the description of the research methodology, data collection and analysis, discussion of the findings, theoretical and, practical implications, limitations, and future research.

2. Theoretical background

2.1. Meta-UTAUT

The emergence of seminal research theories during the last decades allowed researchers to incorporate and advance their findings in technology acceptance. The Technology Acceptance Model (TAM) (Davis, Bagozzi, and Warshaw 1989) was designed to explain information technology acceptance and has been broadly applied in different contexts for understanding users' behaviour of new technologies. Venkatesh et al. (2003) advanced the TAM by developing the Unified Theory of Acceptance and Use of Technology (UTAUT) tailored to organisational contexts. Venkatesh et al. (2003) incorporated additional factors that influence users' acceptance based on a review of eight previous relevant theories, specifically the Theory of Reasoned Action (TRA – Ajzen and Fishbein 1980), Social Cognitive Theory (Bandura 1986), Theory of Planned Behaviour (TPB – Ajzen 1991), TAM model (Davis, Bagozzi, and Warshaw 1989), Motivational Model (Davis, Bagozzi, and Warshaw 1992), C-TAM model combined with TPB (Taylor and Todd 1995), Model of PC Utilisation (Thompson, Higgins, and Howell 1991) and Innovation Diffusion theory (Rogers 1961). UTAUT identifies performance expectancy, effort expectancy, and social influence as predictors of behavioural intention. These factors, together with the facilitating conditions shape use behaviour (Venkatesh et al. 2003).

Nonetheless, later studies unveiled inherent limitations in UTAUT models and suggested areas of improvement (Patil et al. 2020; Tamilmani, Rana, and Dwivedi 2021). Dwivedi et al. (2019) highlighted one of the major constraints: their meta-analytical framework emphasised the importance of introducing attitude as a core construct in the pre-existent UTAUT frameworks. The authors introduced a revised UTAUT model pointing attitude as a construct being central to behavioural intention and use behaviour, partially mediating the effects of the previously established exogenous user factors on behavioural intention, and exerting a direct effect on usage behaviour (Dwivedi et al. 2019). This framework, named meta-UTAUT, is considered a state-of-the-art model of technology acceptance and use since, with the inclusion of attitude, the exploratory power of the model was significantly increased to 45%, compared to the 38% of the baseline model without attitude (Dwivedi et al. 2019).

The importance of attitude on users' intentions towards performing the focal use behaviour during early stages of technology adoption is paramount (Patil et al. 2020). However, extant research on the adoption of chatbots in education has applied or extended the TAM (e.g. Malik et al. 2021) or UTAUT (e.g. Raffaghelli et al. 2022) models, failing to encapsulate the key role of attitude, with one exemption (Khechine, Raymond, and Lakhal 2022). Hence, applying the meta-UTAUT model would be most appropriate to understand the students' adoption of ChatGPT in higher education. This is because, first, it provides the opportunity to treat attitude as a core construct. Second, because this model has not been empirically tested for students' acceptance and use of chatbots in higher education. Indeed, research has applied the meta-UTAUT in contexts such as AI-integrated customer relationship management (Chatterjee et al. 2021), mobile payments and banking (Jadil, Rana, and Dwivedi 2021; Patil et al. 2020; Upadhyay et al. 2022), and tourism adoption (Tamilmani, Rana, and Dwivedi 2021). Nonetheless, prior studies examining chatbot adoption in higher education have primarily applied the TAM and UTAUT models (e.g. Chen, Vicki Widarso, and Sutrisno 2020; Henkel, Linn, and van der Goot 2023; Malik et al. 2021), therefore failing to include individual difference core constructs such as attitude. This study, therefore, operationalises the five significant meta-UTAUT constructs (performance and effort expectancies, social influence, facilitating conditions, and attitude) to identify how such constructs influence students' adoption of ChatGPT in higher education.

2.2. Extended meta-UTAUT

Even though prior research has underlined the significance of factors such as anthropomorphism (Sheehan, Jin, and Gottlieb 2020), trust (Croes and Antheunis 2021; Patil et al. 2020), and design novelty (Mugge and Dahl 2013) in user adoption of new products or chatbots in specific, no prior studies have used these variables to explain students' adoption of chatbots in the higher education context. First, anthropomorphic features have been progressively more apparent across chatbots (Crolic et al. 2022; Haugeland et al. 2022; Sheehan, Jin, and Gottlieb 2020). Chatbot anthropomorphism provides a human context, providing the human-to-machine conversation in a more humanlike manner through intelligent cognitive frameworks (Balakrishnan and Dwivedi 2021b). Chatbot developers usually employ a combination of cues to enhance the humanness of chatbots (Park et al. 2022). Indeed, ChatGPT has been designed to mimic human-like conversation based on user prompts (Euronews 2022). Despite recent research emphasising anthropomorphism within an extended meta-UTAUT framework for the adoption of chatbot-based services (Balakrishnan, Abed, and Jones 2022), research has yet to investigate this attribute within an educational context.

Second, recent research (Choi and Zhou 2023; Croes and Antheunis 2021; Yen and Chiang 2021; Zhang et al. 2023) has underlined the importance of trust in the adoption of artificial intelligence systems and chatbots in specific. Patil et al. (2020) referred to trust as the individual's belief that a party will fulfil their obligations, which is important when users are exposed to a sense of loss of control. Furthermore, the more personalised communication a chatbot can offer, the more people trust the chatbot (Croes and Antheunis 2021). Trust is, in essence, a key factor in establishing a strong emotional bond with novel technologies (Creed, Beale, and Cowan 2015). Interestingly, a benefit of chatbot communication compared to human communication pertains to the chatbots' inability to share secrets, ensuring privacy and anonymity (Joinson and Paine 2007). Based on the above, the question is whether students can trust ChatGPT for their educational activities and whether such trust drives ChatGPT adoption.

Third, a product's design novelty (otherwise named as design newness) (Mugge and Dahl 2013) can influence its adoption. Accordingly, the novelty of the chatbot design can be a key factor motivating the acceptance of interactive technologies such as chatbots. Novel features associated with chatbots, such as ChatGPT, may be relevant, at least for early adopters or innovators (Brandtzaeg and Følstad 2017), and even more prevalent for younger users, such as students. Chatbots have been found to promote the success of students' design behaviour outcomes (Chien and Yao 2022). Nonetheless, the role of chatbot design novelty as a factor driving students' acceptance of ChatGPT remains to be examined.

2.3. Institutional policy

Despite the novel features of ChatGPT, there are voices who are cautiously approaching the use of ChatGPT in higher education settings (Tlili et al. 2023). Any uncritical use of ChatGPT brings several concerns to be considered (Dwivedi et al. 2023). For instance, content bias and discrimination are protuberant in AI and chatbot research (Akter et al. 2021; Stahl et al. 2023), raising questions about institutional policy. Students depend on ChatGPT as a principal assistant for their educational obligations or even entirely rely on ChatGPT-generated content instead of developing their own thinking and understanding of curricula. Such risks pertaining to ChatGPT use that are inconsistent with the intended purpose of higher education highlight the need for new regulations and policies on an institutional level (e.g. Lo 2023). Institutional policy should ensure that the use of ChatGPT is in alignment with the institution's values such as fairness and transparency, without jeopardising effective pedagogy (Lo 2023). Hence, it is critical to first empirically investigate any effects of institutional policy on students' adoption of ChatGPT in higher education.

3. Hypotheses development

3.1. Effects of user factors on attitude towards ChatGPT

Performance expectancy is considered an important variable in the UTAUT framework and assesses the degree to which performance will be improved while acting on information systems (Patil et al. 2020; Venkatesh et al. 2003). Performance expectancy explains the perceived user benefits in performing specific activities (Balakrishnan, Abed, and Jones 2022; Venkatesh et al. 2003; Venkatesh, Thong, and Xu 2012), in this case, the students' benefits in using ChatGPT for their academic activities. In their seminal meta-UTAUT framework, Dwivedi et al. (2019) highlighted performance expectancy as the most significant antecedent positively influencing user attitude. In the field of education, Šumak, Polancic, and Hericko (2010) unveiled performance expectancy as a predictor of students' attitude towards an open-source web-based Virtual Learning Environment. Accordingly, Altalhi (2021) found that performance expectancy significantly influences students' attitude towards massive open online courses in higher education. Nonetheless, research still needs to investigate the effect of performance expectancy on attitude towards emerging higher education chatbots. The following hypothesis is proposed based on the previous discussion:

> Hypothesis 1 (H1): Performance expectancy positively influences student's attitude towards ChatGPT.

Effort expectancy refers to the extent of easiness related with the use of technology (Venkatesh, Thong, and Xu 2012). In this study, effort expectancy refers to the degree to which a student considers the use of ChatGPT to be of low effort. Within the chatbot industry, there is a continuous attempt to reduce the effort to provide incremental value towards brand preference (Cheng and Jiang 2022). To date, conflicting evidence exists on the impact of effort expectancy on attitude. Previous research (e.g. Šumak, Polancic, and Hericko 2010) showed that effort expectancy is not a significant predictor of students' attitude towards the use of mobile or virtual learning environments. Nonetheless, students' perceptions of the easiness of such technologies may have evolved recently, together with the emergence of less complex and more accessible chatbots. For instance, ChatGPT is designed to identify the context of a conversation in order to provide more relevant and accurate responses (Abdullah 2023). Such contextual understanding can make it easier for students to interact with ChatGPT. In addition, Dwivedi et al. (2019) unveiled effort expectancy as a significant predictor of attitude, while Anthony, Kamaludin, and Romli (2023) highlighted effort expectancy as a significant factor that influences attitudes towards adopting technology for educational purposes. Thus, it is important to investigate whether effort expectancy leads to more favourable students' attitude towards ChatGPT. We propose the following hypothesis:

> Hypothesis 2 (H2): Effort expectancy positively influences student's attitude towards ChatGPT.

3.2. Effect of anthropomorphism on attitude towards ChatGPT

Anthropomorphism is generally defined as the attribution of distinctively human-like feelings, mental states, and behavioural characteristics to inanimate objects, animals, and in general to natural phenomena and supernatural entities (Airenti 2015). Anthropomorphism may pertain to hardware and software features that spark an anthropomorphic design (Qiu and Benbasat 2009). The increase in anthropomorphism drives a positive effect in perceived social presence and attitude, which are essential for meaningful human–computer interactions (Araujo 2018). Anthropomorphism has been explored as a key construct in the adoption of chatbots (Balakrishnan, Abed, and Jones 2022; Sheehan, Jin, and Gottlieb 2020), with positive effects on human-AI interaction experiences (Li and Sung 2021). Balakrishnan and Dwivedi (2021b) underlined that intelligent digital assistants and chatbots can lead to a positive attitude. Kim and Im (2023) underlined that anthropomorphism shapes attitudes towards technology, while Martin et al. (2020) found that anthropomorphism is positively associated with attitude towards AI trip advisors. However, no study has directly examined the potential positive relationship between anthropomorphism and attitude towards chatbots such as ChatGPT within a higher education setting. From the above discussion, the following hypothesis is proposed:

> Hypothesis 3 (H3): Anthropomorphism positively influences student's attitude towards ChatGPT.

3.3. Effect of design novelty on attitude towards ChatGPT

Product design features can significantly affect subsequent consumer responses (Bloch 1995. Design novelty, also called design newness, is defined as the deviation in a product design from the existing design state of a certain product category (Mugge and Dahl 2013; Talke et al. 2009). Design novelty is determined by the degree to which the product has attributes in common with the other products of its category. The fewer attributes a product shares with competing products, the greater its degree of design novelty (Loken and Ward 1990). An extrapolation of these theories in the context of chatbot systems highlights the potential role of design novelty for the adoption of ChatGPT in higher education. In the context of chatbots, the definition of design novelty refers to the deviation in the design of a chatbot from existing chatbot solutions. Design novelty in chatbots can be evaluated based on the degree to which a chatbot exhibits unique attributes or features that distinguish it from other chatbot offerings within the same category. In this regard, while traditional chatbots often have limited novel features, ChatGPT is highly adaptable to different contexts, outputs, and communication styles. Its tailor-made responses generated to the specific user, context, and domain can be perceived as a further testament to its innovative design. Brandtzaeg and Følstad (2017) argued that innovative chatbots can satisfy human curiosity and produce more positive user responses. Based on the above arguments, we hypothesise that:

> Hypothesis 4 (H4): Design novelty positively influences student's attitude towards ChatGPT.

3.4. Effect of trust on attitude towards ChatGPT

When interacting with AI technologies, privacy and security concerns have been related to low trust (Miltgen, Popovič, and Oliveira 2013). For this reason, including trust as a predictor of students' acceptance of chatbots may be relevant (Raffaghelli et al. 2022). Trust provides a 'subjective guarantee that consumers obtain a positive experience about the ability, honesty and goodwill' of novel technologies (Patil et al. 2020, 6). Chatbots are not an exemption. Previous research has highlighted that greater trust significantly improved users' attitude (Liébana-Cabanillas, Sánchez-Fernández, and Muñoz-Leiva 2014; Patil et al. 2020). For students to accept and utilise the advantages of chatbots, it is important to introduce trust, in terms of credibility and confidence (Stathakarou et al. 2020). Pesonen's (2021) study revealed that within a sample of Finnish students, a higher level of trust in chatbots correlated with more positive reactions from the students. Hence, we hypothesise that:

> Hypothesis 5 (H5): Trust positively influences student's attitude towards ChatGPT.

3.5. Relationships between user factors

Facilitating conditions depict the importance of organisational and technical infrastructure to support systems use (Dwivedi et al. 2017; Venkatesh et al. 2003) and reflect the consumers' perceived resources that can support in performing a behaviour (Venkatesh, Thong, and Xu 2012). Research has unveiled a significant effect of facilitating conditions on effort expectancy or neighbourhood constructs. For instance, Stefi (2015) underlined that facilitating conditions generate lower perceived effort in the context of developers' acceptance of software components, while Patil et al. (2020) validated the abovementioned relationship as a new internal mechanism within the meta-UTAUT framework, extending its value beyond the traditional scope of the TAM model. The importance of facilitating conditions in shaping effort expectancy is further accentuated by the findings of Tlili et al. (2023). Their study on ChatGPT's application in educational settings sheds light on the multifaceted nature of technology adoption, where ease of use and effectiveness are key considerations for students. Such theoretical grounds support the notion that facilitating conditions, encompassing the technological infrastructure and institutional support, can influence students' perceived ease (i.e. effort expectancy) in using ChatGPT. Based on the above rationale, the following hypothesis is made:

> Hypothesis 6 (H6): Facilitating conditions positively influence student's effort expectancy.

3.6. Effects of user factors on behavioural intention to adopt ChatGPT

Behavioural intention refers to the subjective probability of an individual's engagement in a certain behaviour (Ajzen and Fishbein 1975). Performance expectancy indicates benefits that users perceive from a system, in this case the ChatGPT chatbot. For instance, Than, Kyaw, and Htoo (2021) and Strzelecki (2023) emphasised the impact of performance expectancy in determining students' behavioural intention to use technologies in higher education, while Chao (2019) unveiled performance expectancy as an antecedent of students' behavioural intention for mobile learning in universities. Similarly, Almahri, Bell, and Merhi (2020) underlined the significant relationship between performance expectancy and behavioural intention for chatbot use in the United Kingdom universities. The following hypothesis is proposed:

> Hypothesis 7 (H7): Performance expectancy positively influences student's behavioural intention to adopt ChatGPT.

Effort expectancy is based on the easiness prevailing in the system use. In general, companies aim to reduce the perceived user effort and optimise the value chain process towards gaining a long-term orientation. In the case of chatbots such as ChatGPT, the ease and preciseness in conversation can reduce the perceived effort. Within an educational context, Khechine, Raymond, and Augier (2020) highlighted that a technology's perceived efficiency and effectiveness are critical for users' adoption. ChatGPT could be effective as an alternative for educational activities by offering fast information and reducing the students' efforts (Lo 2023). Than, Kyaw, and Htoo (2021) highlighted that effort expectancy predicts the behavioural intention to use technologies within a higher education context. From the above discussion, the following hypothesis is formulated:

Hypothesis 8 (H8): Effort expectancy positively influences student's behavioural intention to adopt ChatGPT.

Social influence refers to the degree to which consumers perceive that close others, such as family and friends, deem that they should use a particular technology (Venkatesh, Thong, and Xu 2012). It has been argued that social influence affects individual behaviour through mechanisms such as compliance, internalisation, and identification, which can alter the user's belief structure, causing an individual to correspond to potential social status gains (Dwivedi et al. 2019; Kelman 1958). Social influence has been regarded as a critical element to decision-making for people in sociology and in behavioural science and a determinant factor of technology adoption that marketers should consider (Lu 2014). Although social influence has been underlined as a key antecedent of students' adoption of e-learning systems (Salloum and Shaalan 2019), such relationship remains to be examined through a meta-UTAUT perspective in the context of chatbot adoption. We form the following hypothesis:

Hypothesis 9 (H9): Social influence positively influences student's behavioural intention to adopt ChatGPT.

One of the notable highlights of Dwivedi et al. (2019) was that the relationship between facilitating conditions and behavioural intention was missing in the original UTAUT model (Venkatesh et al. 2003). Based on their meta-analytic approach, Dwivedi et al. (2019) suggested its inclusion, in alignment with findings from prior studies (Foon and Fah 2011). While previous research has unveiled the importance of facilitating conditions in shaping behavioural intentions, such relationship has not received proper attention in the context of higher education, with few exemptions (e.g. Salloum and Shaalan 2019). ChatGPT and similar chatbots can facilitate functional conditions and eventually lead to augmented student behavioural intentions. From the above discussion, the following hypothesis is proposed.

Hypothesis 10 (H10): Facilitating conditions positively influence student's behavioural intention to adopt ChatGPT.

3.7. Effect of attitude on behavioural intention to adopt ChatGPT

Attitude refers to the extent of a person's positive or negative feelings about performing a target behaviour (Davis, Bagozzi, and Warshaw 1989). Research related to the different theoretical models (TAM, TRA and TPB) has shown that attitude is an essential pre-requisite of the intention (Liébana-Cabanillas, Sánchez-Fernández, and Muñoz-Leiva 2014). Prior research in meta-UTAUT models has found a significant relationship between attitude and behavioural intention (e.g. Balakrishnan, Abed, and Jones 2022). Kasilingam (2020) found a significant positive effect of attitude on behavioural intention towards smartphone chatbots, while Malik et al. (2021) found a similar effect in the context of learning chatbots for university students. Hence, the following hypothesis is proposed:

Hypothesis 11 (H11): Attitude positively influences student's behavioural intention to adopt ChatGPT.

3.8. Effects of attitude, behavioural intention and facilitating conditions on use behaviour of ChatGPT

Davis, Bagozzi, and Warshaw (1989) demonstrated that attitude directly affected use behaviour. Later studies confirmed this relationship (Adams, Nelson, and Todd 1992; Kim, Lee, and Law 2008; Pijpers et al. 2001) of information system adoption. Furthermore, Venkatesh, Thong, and Xu (2012) established the effect of behavioural intention on use behaviour. Importantly, based on a meta-analysis on 1600 observations on 21 relationships coded from 162 prior studies on acceptance and use of information system and technology innovations, Dwivedi et al. (2019) unveiled the significant effects of both attitude and behavioural intention on use behaviour. On these grounds, Abbad (2021) unveiled behavioural intention as a key predictor of students' usage behaviour of e-learning systems, while Jo (2023) and Strzelecki (2023) found, within Korean and Polish student samples respectively, that behavioural intention influences students' ChatGPT use behaviour. Interestingly, there is no scientific consensus on the measurement of use behaviour. For example, Venkatesh, Thong, and Xu (2012) measured use behaviour based on the use frequency of various systems, but later studies (Sivathanu 2019) preferred a Likert scale, which is also the approach of this study. Given the substantial evidence supporting the significant influence of attitude and behavioural intention on use behaviour in the adoption of relevant technological systems and innovations, the following hypotheses are formulated:

Hypothesis 12 (H12): Attitude positively influences student's use behaviour of ChatGPT.

Hypothesis 13 (H13): Behavioural intention positively influences student's use behaviour of ChatGPT.

Facilitating conditions and behavioural intention, have been proposed to directly influence behaviour (Venkatesh et al. 2003). Dwivedi et al. (2019) empirically reaffirmed the importance of facilitating conditions as a significant predictor of use behaviour. In the context of chatbots, Altalhi (2021) found that facilitating conditions significantly influence students' use behaviour of a higher education massive open online course. Similarly, Abbad (2021) highlighted facilitating conditions as a predictor of students' usage behaviour of e-learning systems, while Anthony, Kamaludin, and Romli (2023) revealed that attitude influenced students' behavioural intentions for blended learning in higher education. We hypothesise that:

Hypothesis 14 (H14): Facilitating conditions positively influence student's use behaviour of ChatGPT.

3.9. The moderating role of institutional policy in the relationship between behavioural intention and use behaviour of ChatGPT

How can institutional policy influence students' adoption of ChatGPT in higher education? In general, institutional theory provides a valuable perspective for understanding the influence of external institutional pressures, such as rules and policies, on organisational behaviour and practices (DiMaggio and Powell 1983). Organisational legitimacy, a fundamental concept in institutional theory, refers to the perceived appropriateness and acceptance of an organisation's actions, behaviours, and practices within its institutional environment (Suchman 1995), as it reflects the degree to which an organisation's actions are seen as valid, desirable, and socially acceptable by its stakeholders and the broader society. From the lens of institutional theory, organisational legitimacy is closely related to the prevailing institutional logics and norms within a specific context (Thornton, Ocasio, and Lounsbury 2012). Institutional logics form the underlying values, beliefs, and assumptions that guide behaviour and decision-making in a given institutional environment. Organisations strive to align their actions and practices with these logics to gain legitimacy and social approval.

In the context of higher education, institutions are governed by formal rules and policies (Burch 2007) that can shape the adoption and use of technological innovations, such as chatbots. These institutional policies reflect the broader institutional norms that shape decision-making and practices within the educational setting (Suchman 1995). The alignment of policies with the prevailing institutional logics and norms in higher education institutions can affect the legitimacy of using chatbots among students. Indeed, research in AI systems has established that the absence of policy can be a major limitation for them with regard to cybersecurity and privacy (Calo 2017). While there is an emerging need for responsible management education in higher education (Azmat, Jain, and Sridharan 2023), issues of bias and discrimination in data and algorithms are often prominent in AI and chatbot research (Akter et al. 2021; Dwivedi et al. 2023). In this regard, institutional policy can refer to realistic and workable moral decisions deriving from understanding and weighing both the opportunities and negative implications of ChatGPT (Dwivedi et al. 2023).

Building upon institutional theory and organisational legitimacy, we posit that institutional policy may act as a barrier, negatively moderating the translation of students' behavioural intentions into actual use behaviour. Policy on students' use of ChatGPT should dissolve doubts about the limits of using ChatGPT as a student that formal university regulations with regards to transparency and fair use should resolved. Importantly, students can perceive policy as a means of institutional behavioural control. Ajzen (1985) introduced behavioural control as a moderator between intention and behaviour. Furthermore, research on the gap between intentions and ethical behaviour in other contexts (e.g. Carrington, Neville, and Whitwell 2010) unveiled that behavioural control moderates the effect of intentions on behaviour. In a similar vein, policy can form barriers to the translation of intentions into use behaviour. The following hypothesis is formed.

Hypothesis 15 (H15): Institutional policy negatively moderates the effect of student's behavioural intention on use behaviour of ChatGPT.

The conceptual framework is given in Figure 1.

4. Materials and methods

4.1. Research design, procedure, and participants

The present research adopted a single cross-sectional research design using survey methodology and addressed to students in the higher education in the Netherlands. Such a research design allowed examining students' attitudes, behavioural intentions and use behaviours at a specific time. Given the rapidly evolving nature of chatbot technology and the continuous commercialisation of ChatGPT versions which might influence adoption patterns, a snapshot of students' perspectives would provide immediate insights on how students engage with AI tools.

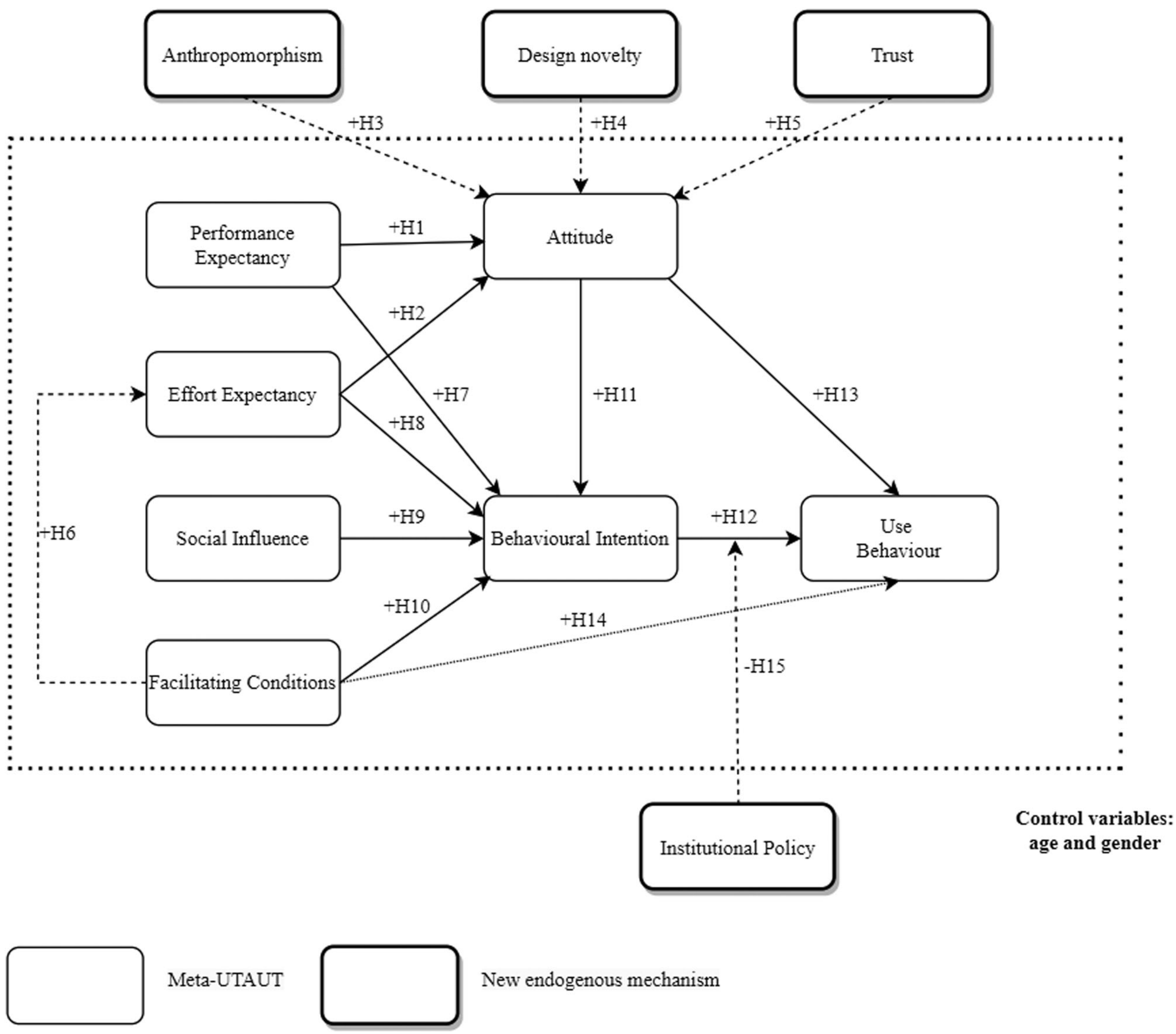

Figure 1. Conceptual framework of students' use behaviour of ChatGPT in higher education.

Note: Continuous lines refer to existing relationships and dotted lines refer to new relationships. Source: authors, adapted from Dwivedi et al. (2019) and Patil et al. (2020).

Before distributing the research instrument, we applied pre-screening criteria to ensure that the participants were students in the higher education and were actively enrolled in academic institutes in the Netherlands. It must be noted that we chose to address educational institutes in all fields, as ChatGPT can be used for the same educational purposes in all contexts. Conducting this research in one (or two) educational institutes would limit the variation in responses, especially in relation to constructs, such as institutional policy which is a key variable of this study. Specifically, the educational landscape of our study's population included students from diverse higher educational institutes in the Netherlands such as Research Universities or Universities of Applied Sciences, in fields such as social sciences and humanities, science, technology, engineering and mathematics (STEM), economics and business, arts and law.

To realise this study, a questionnaire was distributed to 420 participants who completed the study online through the Prolific platform. Also, one screening question was used to identify the representative sample among those 420 participants: 'Have you ever used ChatGPT for an educational purpose' (yes/no)? Given that the questionnaire included questions related to the adoption of ChatGPT in education, as well as perceptions about its actual use, it was of a great importance to collect a final sample of students that had a previous experience with the use of the specific AI tool. In other words, only subjects who have previously used ChatGPT in their educational context were considered reliable and valid for the study. Overall, 355 participants, who affirmed their eligibility by answering 'Yes' to the screening question and successfully passed the attention checks, comprised the final usable sample for this study. This sample was considered representative of our focal population,[1] which encompassed 344,627 students enrolled in university education institutes in the Netherlands in 2022, according to statistics from Statistics Netherlands (Centraal Bureau voor de Statistiek 2023). The study was approved by the institutional Human Research Ethics Committee of TU Delft.

4.2. Instrument and measures

The questionnaire consisted of four parts. The first part included questions in relation to attitude and use behaviour of ChatGPT in education. Our intention in this part was to measure the following constructs: attitude, behavioural intention, and use behaviour. For the measurement of attitude, we adapted the 3-item scale of Balakrishnan and Dwivedi (2021b). To measure the behavioural intention, we used a 3-item scale (Ashfaq et al. 2020; Balakrishnan, Abed, and Jones 2022). For the measurement of use behaviour, we adjusted the scale from Patil et al. (2020) into a 4-item scale. All the items in this part were measured in seven-point Likert scale (1: Strongly disagree – 7: Strongly agree).

The second part of the questionnaire consisted of study constructs measuring the user factors of meta-UTAUT namely, performance expectancy (3-item scale), effort expectancy (4-item scale), facilitating conditions (4-item scale), and social influence (3-item scale) and is derived from previous studies (Venkatesh et al. 2003; Venkatesh, Thong, and Xu 2012). All items in this part were measured in seven-point Likert scale (1: Strongly disagree – 7: Strongly agree).

In the third part, we included questions related to systems factors of meta-UTAUT. Perceived anthropomorphism was a 5-item construct (Balakrishnan and Dwivedi 2021b; Balakrishnan, Abed, and Jones 2022) and trust was a 3-item scale (Patil et al. 2020). Design novelty had 3 items (Mugge and Dahl 2013) and institutional policy had 3 items (self-developed, adjusted from Patil et al. 2020). All items in this section were measured in seven-point Likert scale (1: Strongly disagree – 7: Strongly agree), except for Design novelty, a semantic differential scale. Detailed information on the measurement items of the abovementioned constructs are given in Table 1.

The fourth part of the questionnaire consisted of demographic information, namely, students' gender and age. Gender and age were included as control variables to enhance model variance. Gender was measured as a categorical and age as a continuous variable.

4.3. Analysis

Our study used a two-step Structural Equation Modelling technique (SEM) to examine the proposed research model. We first employed Confirmatory Factor Analysis (CFA) to confirm the reliability, content and discriminant validity of our data. As a part of the CFA analysis, we performed a Common Method Bias test (CMB) to test whether the data were free from any measurement bias. After confirming validity and CMB requirements, SEM and specifically path analysis, was used to test the proposed hypotheses. Maximum Likelihood Method (MLM) was used to estimate the model. Following the direct paths, the moderating effect of institutional policy was also tested in the model. For all the estimation purposes, we used IBM SPSS 26 and STATA 14.

5. Results

5.1. Demographic characteristics and correlation matrix

The final sample consisted of 54.08% male and 45.92% female participants, offering a largely representative gender distribution. The average age of the sample was 22.99 years (SD = 4.35), and this low variation can be explained from the fact that the study was addressed to students in higher education.

Table 2 presents means, standard deviations, and correlations for the key variables. Pearson's r correlation coefficients show moderate correlations among the independent variables.

5.2. Measurement model and common method bias

Before conducting the hypotheses testing, CFA with STATA 14 was used to investigate the distinctiveness between the variables of our research model. At first, we run an 11-factor model (one first order latent construct for each of the 11 variables). An analysis of this model revealed a good fit between the model and the data, $\chi^2(610) = 1{,}484.94$ ($p < 0.001$), $x^2/\text{df} = 2.434$, CFI = 0.93, TLI = 0.91, RMSEA = 0.06, SRMR = 0.06. Then, we ran an alternative 8-factor model (performance expectancy, effort expectancy, social influence, and facilitating conditions were loaded into one factor), an

Table 1. Measurement items.

Construct	Items	Source
Performance expectancy (PE)	I would find ChatGPT useful in my daily academic life. Using ChatGPT would help me accomplish things more quickly. Using ChatGPT for services might increase my student productivity.	Venkatesh et al. (2003); Venkatesh, Thong, and Xu (2012)
Effort expectancy (EE)	Learning how to use ChatGPT would be easy for me. My interaction with ChatGPT would be clear and understandable. I would find ChatGPT easy to use as a student. It would be easy for me to become skilful at using ChatGPT.	Venkatesh et al. (2003); Venkatesh, Thong, and Xu (2012)
Social influence (SI)	People who are important to me think that I should use ChatGPT as a student. People who influence my behaviour think that I should use ChatGPT. People whose opinions I value prefer that I use ChatGPT.	Venkatesh et al. (2003); Venkatesh, Thong, and Xu (2012)
Facilitating conditions (FC)	I have the resources necessary to use ChatGPT as a student. I have the knowledge necessary to use ChatGPT as a student. ChatGPT is compatible with other technologies I use. I can get help from others when I have difficulties using ChatGPT.	Venkatesh et al. (2003); Venkatesh, Thong, and Xu (2012)
Perceived anthropomorphism (PA)	ChatGPT is natural; I do not feel fake about it. ChatGPT is more humanlike. ChatGPT is conscious of its actions. ChatGPT feels lifelike and not artificial. ChatGPT is elegant in engaging.	Balakrishnan, Abed, and Jones (2022); Balakrishnan and Dwivedi (2021b)
Trust (TRU)	I trust ChatGPT to be reliable. I trust ChatGPT to be secure. I trust ChatGPT to be trustworthy.	Patil et al. (2020)
Design novelty (NOV)	I find ChatGPT to be: 1 Old – 7 Novel I find ChatGPT to be: 1 Not original – 7 Original I find ChatGPT to be: 1 Not innovative – 7 Innovative	Mugge and Dhal (2013)
Institutional policy (POL)	There is some authority to approach within the university in case of unfair use of ChatGPT. There is transparency in setting academic rules about the ChatGPT use. Doubts about the limits of using ChatGPT as a student are resolved by formal university regulations.	Patil et al. (2020)
Attitude (ATT)	I like using ChatGPT as a student. I feel good about using ChatGPT. Overall, my attitude towards using ChatGPT in my academic life is favourable.	Balakrishnan and Dwivedi (2021b)
Behavioural intention (INT)	I intend to continue using ChatGPT in the future. I will always try to use ChatGPT in my daily academic life. I will strongly recommend my classmates to use ChatGPT.	Ashfaq et al., (2020); Balakrishnan, Abed, and Jones (2022)
Use behaviour (USE)	I use ChatGPT as a student. I use ChatGPT for my learning activities. I use ChatGPT to fulfil my academic responsibilities. I use ChatGPT to perform my academic assignments.	Patil et al. (2020)

alternative 5-factor model (performance expectancy, effort expectancy, social influence, and facilitating conditions were loaded into one latent factor and perceived anthropomorphism, design novelty, trust and institutional policy were loaded into one latent factor), and a 1-factor model (all variables loaded into one factor). The hypothesised 11-factor model fitted the data significantly better than the 8-factor model (χ^2[639] = 1,769.03 ($p < 0.001$), x^2/df = 2.768, CFI = 0.90, TLI = 0.89, RMSEA = 0.07, SRMR = 0.09), the 5-factor model (χ^2[650] = 1,787.91 ($p < 0.001$), x^2/df = 2.751, CFI = 0.90, TLI = 0.89, RMSEA = 0.07, SRMR = 0.09), and the1-factor model (χ^2[639] = 1,868.12 ($p < 0.001$), x^2/df = 2.856, CFI = 0.89, TLI = 0.88, RMSEA = 0.07, SRMR = 0.09).

In addition, we ran additional analyses to check the robustness of our model in terms of its content and discriminant validity, and the reliability of our latent constructs. Table 3 shows the standardised factor loadings over 0.50 which confirm the content validity requirements (Gefen, Straub, and Boudreau 2000). In addition, the table shows the Cronbach's alpha values above 0.70, which confirms that the scales are reliable and internally consistent (Hair et al. 1992). Finally, Average Variance Extracted (AVE) values, which are a measure of variation explained by the latent variable to random measurement error ranged from 0.55 for performance expectancy and perceived anthropomorphism to 0.87 for social influence, which is higher than the threshold of 0.50 (Fornell and Larcker 1981).

Further to the CFA, the CMB test was performed to understand whether our data were free from common method bias. We implemented the Common Latent Factor (CLF) technique and controlled for the effects of an unmeasured latent factor (Podsakoff et al. 2003). We then compared the standardised estimates of the model with the CLF with the ones of the model without the CLF to check the differences in the factor loadings. The results highlighted that the difference ranged from 0.03 to 0.14, thus satisfying the primary condition of CLF to confirm that the data is free from common method bias issues (MacKenzie and Podsakoff 2012).

Table 2. Correlation and descriptive statistics.

Variable	*M*	SD	PE	EE	SI	FC	PA	TRU	NEW	POL	ATT	INT	USE
PE	5.39	1.30	1										
EE	5.52	1.22	0.536**	1									
SI	3.35	1.66	0.433**	0.310**	1								
FC	5.43	1.20	0.471**	0.659**	0.323**	1							
PA	3.34	1.31	0.407**	0.235**	0.506**	0.259**	1						
TRU	3.91	1.56	0.481**	0.391**	0.436**	0.364**	0.563**	1					
NOV	5.46	1.30	0.334**	0.303**	0.280**	0.292**	0.362**	0.435**	1				
POL	5.22	1.41	−0.137**	0.034	−0.281**	−0.035	−0.206**	−0.215**	−0.154**	1			
ATT	4.55	1.62	0.677**	0.468**	0.575**	0.385**	0.480**	0.512**	0.407**	−0.316**	1		
INT	4.08	1.70	0.659**	0.453**	0.626**	0.424**	0.445**	0.527**	0.358**	−0.270**	0.820**	1	
USE	3.68	1.84	0.596**	0.398**	0.589**	0.340**	0.411**	0.442**	0.316**	−0.241**	0.769**	0.829**	1

Note: PE: Performance expectancy, EE: Effort expectancy, SI: Social influence, FC: Facilitating conditions, PA: Perceived anthropomorphism, TRU: Trust, NOV: Design novelty, POL: Institutional policy, ATT: Attitude, INT: Behavioural intention, USE: Use behaviour.

**$p < 0.01$.

5.3. Structural model

After establishing good model fit indices in our CFA, we performed SEM using STATA 14 software, to examine our research hypotheses. Our research model tested relationships between existing exogenous variables, namely the user (performance expectancy, effort expectancy, social influence, facilitating condition) and additional (anthropomorphism, trust, design novelty, institutional policy) factors of meta-UTAUT with endogenous variables (effort expectancy, attitude, behavioural intention, use behaviour). To examine the moderating effect of institutional policy in the relationship between behavioural intention and use, we created the product term (POL * INT) and examined its effects on the dependent variable. It must be noted that age and gender were used as control variables in our research model. Results of the SEM analysis are presented in Table 4. All coefficients reported are unstandardised unless otherwise stated as standardised.

Hypotheses 1 and 2 proposed a positive relationship between performance expectancy and effort expectancy with attitude. Results showed that both performance expectancy ($\beta = 0.580$, $p < 0.01$) and effort expectancy ($\beta = 0.139$, $p < 0.01$) were positively related with attitude, herewith supporting Hypotheses 1 and 2. In addition, perceived anthropomorphism was positively associated with attitude ($\beta = 0.203$, $p < 0.01$), providing support for Hypothesis 3. Similarly, design novelty and trust were positively and significantly related with attitude ($\beta = 0.144$, $p < 0.01$; $\beta = 0.109$, $p < 0.05$), herewith confirming Hypotheses 4 and 5. The R^2 for attitude was 0.543, which demonstrated that the attitude exhibited 54.3% of the variance in the model.

Hypothesis 6 examined the positive relationship between facilitating conditions as an independent variable and effort expectancy as a dependent variable. Results showed a positive association between the two variables ($\beta = 0.671$, $p < 0.01$), supporting Hypothesis 6. The R^2 for effort expectancy was 0.434, which demonstrated that the facilitating conditions accounted for the 43.4% of the total variance of effort expectancy in the model.

Hypotheses 7–11 examined the relationship of the performance expectancy, effort expectancy, social influence, facilitating conditions, and attitude to behavioural intention. Performance expectancy significantly predicted behavioural intention ($\beta = 0.197$, $p < 0.01$), providing support for Hypothesis 7. On the other hand, effort expectancy was insignificant in building the behavioural intention of ChatGPT ($\beta = -0.029$, $p > 0.05$), rejecting Hypothesis 8. Social influence and facilitating conditions were significantly associated with

Table 3. Robustness checks.

Construct	Items	Mean	St.Dev.	Factor loading	CA	AVE
Performance expectancy	PE1	5.37	1.45	0.88	0.89	0.55
	PE2	5.50	1.39	0.84		
	PE3	5.31	1.46	0.85		
Effort expectancy	EE1	5.67	1.27	0.88	0.94	0.80
	EE2	5.40	1.32	0.90		
	EE3	5.57	1.32	0.90		
	EE4	5.44	1.38	0.90		
Social influence	SI1	3.43	1.77	0.96	0.95	0.87
	SI2	3.34	1.75	0.89		
	SI3	3.27	1.73	0.94		
Facilitating conditions	FC1	5.78	1.39	0.88	0.83	0.59
	FC2	5.74	1.36	0.92		
	FC3	5.35	1.48	0.70		
	FC4	4.85	1.64	0.50		
Perceived anthropomorphism	PA1	3.56	1.62	0.68	0.85	0.55
	PA2	3.40	1.62	0.82		
	PA3	2.66	1.68	0.67		
	PA4	3.17	1.70	0.84		
	PA5	3.92	1.64	0.67		
Trust	TR1	3.93	1.68	0.90	0.92	0.79
	TR2	4.01	1.69	0.84		
	TR3	3.80	1.66	0.93		
Design novelty	NOV1	5.93	1.12	0.54	0.77	0.57
	NOV2	4.94	1.80	0.81		
	NOV3	5.52	1.68	0.88		
Policy	POL1	5.08	1.60	0.80	0.87	0.70
	POL2	5.53	1.50	0.87		
	POL3	5.06	1.62	0.84		
Attitude	ATT1	4.73	1.79	0.88	0.93	0.81
	ATT2	4.38	1.73	0.88		
	ATT3	4.54	1.69	0.94		
Behavioural Intention	INT1	4.70	1.90	0.87	0.90	0.74
	INT2	3.56	1.85	0.84		
	INT3	3.98	1.84	0.87		
Use Behaviour	USE1	4.09	2.09	0.91	0.94	0.78
	USE2	3.92	2.03	0.86		
	USE3	3.41	1.95	0.91		
	USE4	3.31	1.97	0.86		

Note: CA represents 'Cronbach's Alpha'; AVE represents 'Average Variance Extracted'.

behavioural intention ($\beta = 0.221$, $p < 0.01$; $\beta = 0.114$, $p < 0.05$), herewith confirming Hypotheses 9 and 10. Finally, attitude was a significant predictor for the behavioural intention of ChatGPT in education ($\beta = 0.595$, $p < 0.01$), supporting Hypothesis 11. The R^2 for behavioural intention was 0.768, which showed that the behavioural intention exhibited 76.8% of the variance in the model.

Table 4. Results of the structural model.

Hypotheses	Exogenous variable	Endogenous variable	Model coefficients	R^2
Hypothesis 6	Facilitating conditions	Effort expectancy	0.671**	0.434
Hypothesis 1	Performance expectancy	Attitude	0.580**	0.543
Hypothesis 2	Effort expectancy		0.139*	
Hypothesis 3	Perceived anthropomorphism		0.203**	
Hypothesis 4	Design novelty		0.144**	
Hypothesis 5	Trust		0.109*	
Hypothesis 7	Performance expectancy	Behavioural Intention	0.197**	0.768
Hypothesis 8	Effort expectancy		−0.029	
Hypothesis 9	Social Influence		0.221**	
Hypothesis 10	Facilitating conditions		0.114*	
Hypothesis 11	Attitude		0.595**	
Hypothesis 12	Behavioural Intention	Use Behaviour	0.935**	0.805
Hypothesis 13	Attitude		0.340**	
Hypothesis 14	Facilitating conditions		−0.057	
	Policy		0.250*	
Hypothesis 15	Policy * Behavioural intention		−0.051*	
	Age		−0.008	
	Gender		0.086	

*$p < 0.05$.
**$p < 0.01$.

Hypotheses 12–14 examined the effects between behavioural intention, attitude and facilitating conditions with the ultimate dependent variable, use behaviour. Results showed that the behavioural intention significantly related with use ($\beta = 0.935$, $p < 0.01$), supporting Hypothesis 12. Similarly, attitude positively predicted use behaviour ($\beta = 0.340$, $p < 0.01$), herewith confirming Hypothesis 13. On the other hand, Hypothesis 14 was rejected, as facilitating conditions was not significantly associated with the dependent variable ($\beta = -0.057$, $p > 0.05$). The R^2 for use behaviour was 0.805, demonstrating that use behaviour exhibited 80.5% of the variance in the model.

Hypothesis 15 examined the potential moderating of institutional policy in the relationship between the behavioural intention and use behaviour. Results showed that there was a negative and significant moderating effect of policy in the above-mentioned relationship ($\beta = -0.051$, $p < 0.05$). In other words, the more the policy perceptions from students increase, the more the relationship between behavioural intention and use behaviour will decrease.

Finally, our results did not demonstrate any significant relationships between age and gender with the use behaviour ($\beta = -0.008$, $p > 0.05$; $\beta = 0.086$, $p > 0.05$).

6. Discussion

In an era of increasing digitalisation, advanced chatbots such as ChatGPT offer novel opportunities in the context of higher education transformations. Yet, using such chatbots does not come without risks (Dwivedi et al. 2023). Therefore, it is important to highlight the factors predicting student's adoption of ChatGPT in higher education. The present research operationalised and extended the meta-UTAUT framework (Dwivedi et al. 2019) to investigate the impact of established and additional exogenous factors on attitude, behavioural intention and use behaviour of students in higher education institutions in the Netherlands who are using ChatGPT. These additional exogenous factors are anthropomorphism, design novelty and, trust and institutional policy. Hypotheses 1–5 investigated the role of user and additional exogenous factors to attitude, H6 examined the relationship between user factors, while Hypotheses 7–11 investigated the role of user factors and attitude towards behavioural intention. Hypotheses 12–14 examined the relationship of behavioural intention, attitude and facilitating conditions with use behaviour. Hypothesis 15 unveiled the moderating role of institutional policy.

Results from Hypotheses 1–5 demonstrated the exogenous factors that significantly predict students' attitude towards ChatGPT. Specifically, performance expectancy and effort expectancy lead to a positive attitude towards ChatGPT, aligning with previous literature findings (Balakrishnan, Abed, and Jones 2022; Venkatesh, Thong, and Xu 2012). In other words, students perceive ChatGPT as a tool that it is relatively easy to use, and that can potentially enhance their academic performance and learning outcomes. Our findings also showed that anthropomorphism, design novelty and trust positively associated with attitude. The positive effect of anthropomorphism agrees with previous evidence (Balakrishnan, Abed, and Jones 2022) and implies that when students attribute human-like characteristics to ChatGPT, then the latter is perceived as a more relatable and approachable tool. At the same time, we found that the design novelty of chatbots can lead to positive user responses. In the educational context, students are likely to embrace ChatGPT as an innovative tool with high design novelty characteristics (Mugge and Dahl 2013), which can foster attitude. In accordance with findings from other contexts (Patil et al. 2020), our study also showed that trust positively relates with attitude towards ChatGPT. In other words, when students perceive ChatGPT as a trustworthy and reliable tool, they are more likely to develop positive attitude towards its use.

The confirmation of Hypothesis 6 showed that facilitating conditions positively influence effort expectancy. This finding aligns with previous evidence (Patil et al. 2020) and suggests that having access to better resources, facilitates a better and more effortless student experience of ChatGPT. It is expected that, when students are provided with technical infrastructure and ICT support, as well as sufficient knowledge to use such a tool, its perceived ease of use will be much higher.

Results from Hypotheses 7–11 showed the effects of user factors and attitude towards behavioural intention. Specifically, performance expectancy, social influence and facilitating conditions positively predicted behavioural intention, supporting the findings of previous scholars (Dwivedi et al. 2019; Venkatesh, Thong, and Xu 2012). In the context of education, students' belief that ChatGPT will improve their academic performance, together with the positive recommendations from peers and easy access to resources, result in an increased inclination towards to use of the specific AI tool. On the other hand, effort expectancy was not found to positively affect behavioural intention, suggesting that the perceived ease of using ChatGPT is not a driving factor of an actual intention to use it. Our study also showed a positive effect of attitude on behavioural intention, confirming that attitude is a necessary pre-condition of the intention (Balakrishnan, Abed, and Jones 2022; Liébana-Cabanillas, Sánchez-Fernández, and Muñoz-Leiva 2014; Patil et al. 2020).

Results of Hypotheses 12 and 13 showed that behavioural intention and attitude positively predict use behaviour towards ChatGPT, aligning with previous literature findings (Balakrishnan, Abed, and Jones 2022; Patil et al. 2020). In other words, students that develop more positive attitude and possess a higher intention to use ChatGPT for their educational purposes, are more likely to engage in its actual use. On the other hand, the rejection of Hypothesis 14, did not support a significant effect of facilitating conditions on use behaviour, contradicting previous evidence (Dwivedi et al. 2019). This suggests that although high facilitating conditions associated with positive user experiences (e.g. H6), this does not translate into an enhanced actual use of ChatGPT. Additional – contextual or individual – factors, might be more influential towards the adoption of such AI tools in educational settings.

The confirmation of Hypothesis 15 demonstrated a negative moderating effect of institutional policy as a means of behavioural control (Ajzen 1985) on the association between behavioural intention and use behaviour. Our study suggests that although students' high behavioural intention leads to higher use behaviours, this effect will attenuate, because of perceived regulations and institutional policies. This finding aligns with the broader context of the education system facing a paradox concerning AI in various educational settings. While AI is recognised as paramount for generating high-quality educational outcomes, the extensive collection and analysis of personal data about learners are subjects of considerable concern for human-rights advocates (Nguyen et al. 2023). As a result, and in line with previous literature (Lo 2023; Spivakovsky et al. 2023), this study emphasises the need to create institutional policies of a higher education institution regarding the use of AI tools. Specifically, stricter institutional policies in relation to the transparency and fair use of ChatGPT might cause limit in the adoption of such tools in the context of education. While our manuscript addresses the impact of institutional policies on chatbot adoption within higher education settings, it is important to recognise that the challenges and opportunities associated with the use of ChatGPT might vary across diverse educational settings, including primary and secondary education. For example, ethical challenges may be prevalent in higher education, whereas concerns in early childhood contexts might relate to issues of accessibility, affordability, and accountability (Luo et al. 2024).

6.1. Theoretical implications

This research offers significant contributions to the existing literature. First, to our knowledge, this is the one of the first empirical studies that highlight the factors which significantly predict students' adoption of ChatGPT in higher education, hence advancing our understanding of technology-enhanced learning and human-AI interaction in this context. Our findings enrich and extend the research of Jo (2023) and Strzelecki (2023), who unveiled the effects of habit, performance expectancy, hedonic motivation, personal innovativeness, individual impact, and utilitarian benefits on students' behavioural intentions and use behaviour, by providing deeper insights into additional factors influencing students' adoption of ChatGPT in higher education.

Second, this study refines the meta-UTAUT model by positioning attitude as a core construct in understanding ChatGPT adoption in educational settings, a perspective not fully explored in prior research. For instance, while Bonsu and Baffour-Koduah (2023) primarily focused on perceptions and behavioural intentions, Strzelecki (2023) on the antecedents of behavioural intention and use behaviour, and Tlili et al. (2023) on qualitative aspects of ChatGPT interactions, our research extends the meta-UTAUT model (Dwivedi et al. 2019) with additional exogenous factors, thus providing a more holistic view of the adoption of chatbots in the context of education. By including anthropomorphism, design novelty and trust as additional constructs along the meta-UTAUT model, we propose a new endogenous mechanism and an association between such external factors with endogenous variables, namely, attitude, behavioural intention and use behaviour.

Third, the study also extends the available knowledge in the area of institutional theory (DiMaggio and Powell 1983) by exploring its applicability in technology-based conversations. Specifically, institutional policy is introduced and empirically confirmed as a moderating factor in the meta-UTAUT framework, specifically in the relationship between behavioural intention and use behaviour. The negative moderating effect of institutional policy is in accordance with the concept of organisational legitimacy, within the context of institutional theory. Under the lens of this theory, universities, as organisations, conform to values and norms to maintain their legitimacy (Thornton, Ocasio, and Lounsbury 2012). By implementing institutional policies, universities want to uphold their academic integrity, ensure fairness, and address potential ethical concerns regarding the use of ChatGPT in the context of higher education. Such an implementation restricts students' use behaviour, showing the extent to which institutional forces influence their actions.

In addition, the specific finding provides useful theoretical implications under the lens of Responsible Research and Innovation (RRI) (Stilgoe, Owen, and Macnaghten 2013). Our findings add to the scholarly discussion on RRI, suggesting a multi-stakeholder approach involving collaboration between educational institutions and policymakers. It is paramount that institutions and policymakers foster a fair, transparent, and ethically acceptable use of ChatGPT by implementing a clear regulatory framework that will ensure the responsible adoption of the tool by students. Only in that way will students be able to fully grasp the benefits of ChatGPT in education and use it as a tool that will maximise their academic performance and learning outcomes. Finally, as proposed by the meta-UTAUT framework (Dwivedi et al. 2019), this study reaffirms the core importance of attitude in the adoption of chatbots within a higher education context.

6.2. Practical implications

The results derived from the study provide valuable insights to chatbot designers and product managers, professionals interested in the psychological impact of chatbots in human behaviour, and institutional managers and policymakers. First, it is important to of consider, apart from the established user factors, also other exogenous factors while designing service chatbots. Specifically, the role of anthropomorphism and design novelty is evident as these factors are related to attitude towards ChatGPT. This result also enhances the discussion on the possibilities of investing in design novel interfaces and incorporating more anthropomorphic conditions. Nonetheless, it is also equally important to respond to the expected user trust during the use experience of ChatGPT. In this regard, the designers and product managers of ChatGPT and similar advanced chatbots should focus not only in highlighting the usefulness or ease (i.e. performance and effort expectancy) of using the chatbot, but also circulate that ChatGPT is trustworthy, and without privacy or security concerns.

Also, educational institutes should foster a positive social influence and, in that way, encourage students' intention to embrace ChatGPT as a valuable learning tool. For example, educational institutes could encourage instructors to openly discuss ChatGPT in their courses and emphasise the importance of academic honesty. Such dialogues help create a balanced understanding among students, ensuring they are aware of both the advantages and the ethical considerations of using ChatGPT.

It is vital to recognise the role of solid institutional policies in shaping student interactions with and adoption of chatbots such as ChatGPT. Academic institutions must consider the implications of ChatGPT use and monitor its alignment with their educational goals. If it is observed that students are overly dependent on ChatGPT, using it as a primary tool for completing educational tasks rather than developing their own critical thinking and understanding, this calls for policy interventions. In scenarios as such, institutional policymakers should aim to align the use of ChatGPT with the institution's mission and values by implementing rules and regulations that balance students' intentions to use ChatGPT with the necessity of maintaining academic integrity and fostering independent learning.

6.3. Conclusion, limitations, and future research

This research examined the factors influencing students' adoption of ChatGPT in higher education. Such investigation can yield substantial contributions to the field, given the unprecedented functionalities and potential of ChatGPT compared to preexistent chatbots utilised in higher education (Pérez, Daradoumis, and Puig 2020). It is conclusive that existing and additional exogenous factors contribute more to building attitude and continuation intention towards chatbots. The results of this research highlight the paramount importance of the exogenous factors of anthropomorphism, design novelty and trust towards ChatGPT, and the need to incorporate policy measures if academic institutions wish to decrease the adoption of ChatGPT in higher education. Hence, this study can provide meaningful insights to product managers, designers, institutional policymakers, and education managers.

This study comes with limitations. First, although using a cross-sectional methodology was considered appropriate for this study, such a design would make it challenging to provide generalisable conclusions and establish causal inferences. Future researchers should explore the evolving relationship students have with ChatGPT and similar technologies at different points in time through longitudinal studies (e.g. Polyportis 2024). Observing changes over time would offer valuable insights into the progression of students' perceptions and usage behaviour and also yield interesting insights for educational institutions and developers to refine their strategies and improve the student-to-AI interaction within the context of higher education.

Second, while self-reporting is an accepted and practical method in survey-based research, it may not comprehensively capture the complex nuances of students' interactions with ChatGPT. Future research can employ mixed-method approaches, offering deeper insights on how students interact with and perceive chatbots such as ChatGPT. Also, objective measures (e.g. student performance metrics) could be used to mitigate such subjectivity issues.

Also, future research may test the conceptual framework in other contexts to reveal how varied cultural and educational settings influence ChatGPT's adoption and utilisation. Such comparative studies would enhance our understanding of global patterns in technology acceptance and facilitate developing inclusive technologies that are sensitive to the educational needs and cultural nuances of students worldwide. At the same time, exploring such relationships in diverse educational environments would provide a more holistic understanding of the challenges and opportunities associated with the implementation of specific institutional policies.

Furthermore, although the study's research model showed high variance, future research can extend the findings of the present research on the application of the meta-UTAUT framework by integrating additional variables. For example, measuring individual differences among students, such as technology anxiety (Meuter et al. 2003), and examining if such differences influence students' adoption could be meaningful future research avenues.

Given the escalated societal interest in AI chatbot adoption, the findings of the present research contribute to our understanding of the factors that predict students' acceptance of emerging chatbots, thus holding significant value for academic scholars and industry practitioners seeking to comprehend the factors shaping chatbot acceptance.

Note

1. According to Krejcie and Morgan (1970), for studies in the field of behavioural and social sciences, a sample of 384 subjects is sufficient for a population of 1,000,000 (0.0384% of a population). In our study, the sample size represents approximately 0.103% of the student population which is about 2.68 times more than the percentage recommended by Krejcie and Morgan (1970).

Disclosure statement

No potential conflict of interest was reported by the author(s).

Informed consent

Informed consent was obtained from all individual participants included in the study.

Data availability statement

The data used to support the findings of this study are available from the corresponding author upon request.

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