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Chatbots for Academic Services in Higher Education: Students' Perceptions and Acceptance

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Master in Business Analytics

Supervisor:
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BUSINESS SCHOOL

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No Navio, o sol põe-se devagar,
O Bar da AE deixa a saudade ficar.
No Pátio 1, ecos de festas no ar,
Na sala de estudo, a falar sem parar.

Pelo túnel, passos que vão partir,
Mas nas memórias, sempre vão existir.
Fim de um ciclo, um novo começar,
Pronto para um novo Pátio explorar.

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Thank you.

Resumo

A crescente integração da inteligência artificial no ensino superior tem originado novas oportunidades para apoiar os estudantes através de soluções automatizadas, personalizadas e escaláveis. Entre estes desenvolvimentos, os *chatbots* têm ganho maior popularidade como ferramentas interativas capazes de auxiliar em tanto tarefas administrativas, como académicas. Apesar da sua crescente utilização, as opiniões dos estudantes relativamente ao valor global, utilidade, usabilidade e confiança nos *chatbots* em contexto académico determinam o seu nível de adoção. O presente estudo combina as perspetivas do *Value-based Adoption Model (VAM)* e do *Technology Acceptance Model (TAM)* para analisar os fatores que influenciam a aceitação dos estudantes em relação aos *chatbots*.

Os dados foram recolhidos através de um estudo quantitativo, recorrendo a um questionário online distribuído a estudantes universitários portugueses. Foram utilizadas escalas validadas para medir construtos como utilidade percebida, facilidade de utilização, prazer, risco, valor, atitude e intenção comportamental. O IBM SSPSS Statistics 29 e 30 foram utilizados para análises estatísticas e inferenciais e o SmartPLS aplicado para a análise PLS-SEM, com o intuito de avaliar as hipóteses e testar a validade do modelo.

A compreensão da aceitação de *chatbots* está ligada à relação complexa entre elementos cognitivos, emocionais e de risco. O valor é um mediador chave, enquanto a facilidade de uso reforça a utilidade percebida e as análises de valor são influenciadas pelas atitudes relacionadas com o risco. Através da junção destas dimensões, este estudo fornece uma orientação importante para instituições que procurem aumentar as interações com os estudantes e a adoção de tecnologias.

Palavras-chave: Chatbots, Ensino Superior, Technology Acceptance Model, Value-based Adoption Model, Inteligência Artificial na Educação

Códigos JEL: I23, O33

Abstract

The increasing integration of artificial intelligence in higher education has created new opportunities for assisting students with automated, customized and scalable solutions. Among these developments, chatbots are becoming increasingly more popular as interactive tools that can help with administrative and academic work. Despite their increasing popularity, students' opinions about chatbots for academic services overall worth, usefulness, usability and trustworthiness will determine how well they are adopted. For the purpose of tackling this problem, this study combines the perspectives of the Value-base Adoption Model (VAM) and the Technology Acceptance Model (TAM) to examine the elements affecting students' acceptance of chatbots.

Data were collected through a quantitative study using an online questionnaire distributed to Portuguese university students. Validated scales were used to measure constructs such as perceived usefulness, ease of use, enjoyment, risk, value, attitude and behavioural intention. IBM SPSS Statistics 29 and 30 were used for statistical and inferential analysis, and SmartPLS software was employed for PLS-SEM analysis to evaluate the hypothesis, reliability and validity testing.

The understatement of chatbot acceptance is linked to the complex relation between cognitive, emotional and risk elements. Value is a key mediator, while ease of use reinforces the perceived usefulness, and value judgments is influenced by enjoyment and risk related attitudes. Through the incorporation of these dimensions together, the study provides a valuable guidance for institutions that seek to enhance student engagement and technology adoption.

Keywords: Chatbots, Higher education, Technology Acceptance Model, Value-based Adoption Model, Artificial intelligence in education

JEL Codes: I23, O33

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List of Abbreviations and Acronyms

AI - Artificial Intelligence

ATT – Attitude Toward Use

AVA - Advising Virtual Assistant

AVE – Average Variance Extracted

BE&L - Business, Economics and Law

BI - Behavioural Intention

CR – Composite Reliability

Et al. – Et alia

FAQ – Frequently Asked Questions

H - Hypothesis

H&LS - Health and Life Sciences

HTMT - Heterotrait-Monotrait Ratio

LLM – Large Language Models

NLP - Natural Language Processing

NLU - Natural Language Understanding

PE - Perceived Enjoyment

PEOU - Perceived Ease of Use

PLS-SEM - Partial Least Squares Structural Equation Modeling

PR – Perceived Risk

PU - Perceived Usefulness

PV – Perceived Value

RAG – Retrieval-Augmented Generation

RQ – Research Question

SD – Standard Deviation

SE – Standard Error

SRL – Self-regulated Learning

SSH&A - Social Sciences, Humanities and Arts

TAM – Technology Acceptance Model

VAM – Value-based Adoption Model

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CHAPTER 1

1. Introduction

This introduction chapter establishes the foundation for the dissertation by contextualizing the study within the broader context of artificial intelligence (AI) in higher education, highlighting the rise of chatbots as instruments that can enhance both academic and administrative services. It also addresses the increasing significance of interpreting students' perceptions of these technologies, while presenting the theoretical framework of the study, specifically the integration of the Technology Acceptance Model (TAM) and Value-based Adoption Model (VAM). Additionally, it outlines the research problem, objectives and questions while highlighting the academic and practical significance of the study.

1.1. Theme Contextualization

In recent years, AI has become one of the most transformative forces shaping higher education (Zawacki-Richter et al., 2019). It is now an important support for teaching through intelligent tutoring and automated feedback systems (Wang et al., 2024), learning through adaptive and personalized instruction (Liu et al., 2018), and administration through predictive analytics and virtual assistants (Al-Maroof et al., 2021) in real-world contexts, going beyond theoretical studies. There has been a rapid expansion and institutionalization that defined AI in the twenty-first century, with technologies, such as deep learning, machine learning, and natural language processing (NLP) becoming essential in scholarly and practical applications (Liu et al., 2018). The number of breakthroughs in pre-trained models in the past decade has been astounding, and these are a key enabler of AI to be able to deliver increasingly accurate, adaptive and context aware solutions (Shao et al., 2022).

Regarding this technology evolution, chatbots unfolded as very powerful tools, that enabled communication and interaction with students, while using natural language and providing immediate and personalized information (Ula et al., 2023). These chatbot systems have a particular relevance for higher education as they enable more efficient routine questions management, the improvement of quality in academic services and the reduction of the amount of work (Ula et al., 2023). Large language models (LLM) and retrieval-augmented generation (RAG) have recently been combined to increase chatbots' ability to offer dependable and context-sensitive assistance, and through this, it enables enhancing of their role in the innovation of education (Mesquita et al., 2025).

Despite these developments, the students' perceptions of these technologies are equally as important to their effective adoption as technical proficiency. Research indicates that students' trust, views of the systems' utility, and overall value are significantly connected with the long-term efficacy of AI integration in education (Liu et al., 2018).

1.2. Problem and Research Questions

The integration of chatbots in the classroom is not merely a technological issue, as it presents a socio-psychological challenge, as students' willingness to adopt these technologies is contingent upon their perceptions of utility, usability and also the balance between perceived value and potential risk (Al-Abdullatif, 2023). The success of academic chatbots resides on whether users trust and value them as trustworthy support systems in addition to their technical capacity to provide accurate information, as Ula et al. (2023) note. Therefore, it is essential for higher education institutions to comprehend these perceptions to develop and deploy chatbot solutions that students will find appealing (Liao et al., 2022). Through the application and expansion of theoretical models, specifically, the VAM (Kim et al., 2007) and the TAM (Davis, 1989), in the context of higher education, this research has the objective to contribute by offering a broader understanding of how risk-based, cognitive, and emotional factors can influence adoption.

Based on this study motivation, this dissertation addresses the following research question: What factors make a student intend to use a chatbot for academic services?

1.3. Research Goals and Contributions

The primary objective of this dissertation is to examine how students view chatbots for academic services and determine the elements that have the most impact on their acceptance and behavioural intentions in order to answer the research questions. The study specifically aims to achieve the following goals:

- Identify which constructs emerge as the strongest predictors of students' behavioural intention.
- Examine the relationships between ease of use, usefulness, value, enjoyment, risk, attitude and intention to use chatbots in an administrative context, through a conceptual model.
- Evaluate the role of perceived value as a mediator in connecting emotional and cognitive-risk perceptions with adoption outcomes.

- Propose practical recommendations for higher education institutions regarding the design and implementation of chatbots that maximize acceptance by students.

The scope of this dissertation is to give significant and practical insights for higher education institutions that are seeking to be more involved in enhancing students' involvement with the use of digital transformation. There are other stakeholders that can take advantage of the findings of this research, for example, technology developers can understand the perception of students and focus on efficiency and good conversational interfaces. Policymakers and other education leaders can also take advantage by understating how AI can be responsible and ethical incorporated in an education context. This study aims to align institutional priorities with the growing expectations of students who are becoming digitally native.

1.4. Methodology Overview

This study employs a quantitative research design to empirically evaluate the connections outlined in the research proposed conceptual model. It applies a deductive methodology based in recognized theoretical frameworks, specifically the TAM and VAM, to test the proposed hypotheses.

Data was gathered using a structured online questionnaire administered to Portuguese university students. This instrument comprised of two components, the demographic data and the measurement items derived from TAM and VAM scales. The dataset was analyzed using IBM SPSS Statistics 29 and 30, and the model correlations using the SmartPLS software.

1.5. Study Structure and Organization

There are six chapters in this dissertation. After this introduction, the literature review is presented in Chapter 2, which covers the theoretical underpinnings of chatbot history, examples of chatbots for academic services and TAM and VAM as well as how they are applied to the adoption of educational technologies. This chapter also includes the formulation of the hypothesis. The study methodology includes data gathering techniques, and statistical methodologies used, is covered in detail in Chapter 3. The findings are presented in Chapter 4, which also includes the results of the hypothesis test. The results are further discussed in Chapter 4, along with their theoretical and practical implications. Chapter 5 concludes the dissertation by providing a summary of the key findings, delineating contributions and limitations, suggesting areas for further research, and offering recommendations for organizations aiming to effectively integrate chatbots into higher education.

CHAPTER 2

2. Literature Review

The advancement and integration of chatbots have been a key aspect in revolutionizing students' interactions with digital systems, especially in the education context (Al-Abdullatif, 2023). These tools are also becoming increasingly popular as support for teaching (Wang et al., 2024), administration (Al-Maroof et al., 2021), and academic services (Ula et al., 2023), mainly because of recent developments in artificial intelligence and NLP. These are being developed as viable and promising alternatives for optimizing institutional processes and encouraging more self-directed and personalized learning, as well as its integration on academic services (Liao et al., 2022, Al-Abdullatif, 2023).

Accordingly, this chapter seeks to contextualize the phenomenon of chatbots in academia by assessing the literature on this subject. It will focus on stating discussion on fundamental principles, the historical evolution of chatbots, major uses and case-studies in education, the technology it utilizes, and their advantages and disadvantages. The review's scope is to uncover significant case studies and future trends which influence their function in higher education institutions. Throughout, it conducts an organized investigation of existing literature to systematize and reflect on this subject.

2.1. Chatbots: Historical Background and Evolution

The term "chatbot" derives from "chat" and "bot," from Michael Mauldin in 1994, associated it with a conversational agent designed to simulate human conversation. In 1966, the first chatbot, ELIZA, was created by Joseph Wizenbaum and achieved famous as it echoed interlocutors' statements back as questions, with an ironic tone. Another chatbot platform that gained substantial popularity was PARRY, created in 1972 by Kenneth Colby for simulations on psychology-related topics (Brandtzaeg & Følstad, 2017; Rudolph et al., 2023).

In the 1990s, ALICE (Richard Wallace, 2009) appeared as a pattern-matching chatbot utilizing Artificial Intelligence Markup Language, later winning the Loebner Prize three times and being regarded as the "most human computer." SmarterChild (Brandtzaeg & Følstad, 2017) was developed for messenger programs in 2001, followed by the rise of virtual personal assistants like Apple Siri, Microsoft Cortana, Amazon Alexa, Google Assistant, and IBM Watson (Adamopoulou & Moussiades, 2020).

Earlier chatbots relied heavily on pattern matching and predetermined responses, answering only when a user's input matched recorded question and answer pairs, which was a method that struggled to convey meaning beyond surface form (Nuruzzaman & Hussain, 2018). Cleverbot is an example of data-collection turn, as it saves conversations and responses by accessing how past users responded to comparable inputs, even though its outputs might be unpredictable, with lose meaning, and falter over prolonged dialogues (Adamopoulou & Moussiades, 2020). As deep learning gained popularity, end-to-end neural networks began to align with template-based approaches, causing chatbots to shift toward generative models (Shao et al., 2022). Modern work uses sequence-to-sequence structures, attention, and large-scale training to generate longer, more acceptable responses (Shao et al., 2022). Researchers also emphasize repetition in maximum-likelihood training and propose reinforcement learning style objectives to help maintain discussion and better correspond with conversational goals (Vinyals & Le, 2015, Li et al., 2016). Dialogue managers in response-generated systems work together to coordinate template-based, retrieval-based, generative, and search-engine models to produce flexible and coherent interactions (Nuruzzaman & Hussain, 2018). Together, these advancements reflect the field's transition from handwritten rules to neural, data-driven discourse, while leaving unresolved questions about context, coherence, and diversity (Nuruzzaman & Hussain, 2018).

Chatbots have evolved in a substantial way, over the last decade, especially because of relevant developments in NLM like BERT (Devlin et al., 2019), GPT (Brown et al., 2020), T5 (Raffel et al., 2020), and XLNet (Yang et al., 2020). The change between rule-based bots to generative AI models were important to allow more natural, and more human interactions, which resulted in increased application in domains such as education (Al-Abdullatif, 2023), administration (Al-Maroof et al., 2021), and even government services (Jiang et al., 2023). The post-pandemic period has expedited adoption, with an increased emphasis on ethics, data protection, and cultural inclusiveness (Suryanto et al., 2023).

2.2. Chatbots in the Academic Context

Given the growing discussion of chatbots' role in academia (Al-Abdullatif, 2023, Ula et al., 2023), it is important to consider their general applications in teaching. At a basic level, they can promote personalized instruction and serve as an online instructor by responding to students' inquiries (Wang et al., 2024). ChatGPT can assist teachers in developing course instructional resources, and evaluation activities, as well as producing material, including unique assessments, and transforming existing materials into an AI-based chatbot-compatible format (Gill et al., 2024). It can also assist students improve their phrases, exercise pronunciation and terminology, understand sentence structure, and get real-time interpretations (Gill et al., 2024).

ChatGPT can function as a virtual instructor and self-study tool, answering students' questions and generating resources for a more individualized learning environment (Gill et al., 2024). At the same time, there were some significant risks identified, which are, outputs being inaccurate, biased, outdated, or fabricated, which also relates to academic-integrity concerns arising because AI-generated text has the capacity to bypass similarity detectors and because of this educators may struggle to distinguish between AI and human-written work (Rudolph et al., 2023). As a result, it is suggested using the tool with caution, such as drafting or refining text and prompting further questioning and reasoning, rather than allowing it to replace students' critical thinking, and updating institutional policies and assessment designs to address detection limits and misuse (Lo, 2023).

There are numerous case studies using chatbots in academic settings. Essel et al. (2022) evaluated the effectiveness of the "KNUSTbot" in the context of a Ghanaian higher education institution. This chatbot was integrated into a programming and multimedia course and used NLP to address open-ended inquiries. The training process of this chatbot involved approximately a thousand questions, which were previously made to the university. An experience was elaborated, with the division of the sample of 68 undergraduates into an experimental and control group, and the group that used the chatbot had much higher scores, with positive feedback about is usability and rapidness of responses, as well as it showed relevant information.

CiSa is a chatbot created exclusively for overseas students at Kookmin University (Heo & Lee, 2019). Its primary purpose is to increase access to critical information regarding academic life and the also the campus, with its focus being the cultural and linguistic differences. It addresses academic and administrative issues like calendars, housing, events, and the library. Several polls and conversations with overseas students revealed challenges getting information on existing platforms, which prompted the development of the chatbot, and this approach allowed every learner to get the help they needed, regardless of time, location, or language (Heo & Lee, 2019).

Telkom University (Purwokerto) also created SiAkif for student help. Its primary goal is to address delays in responses from academic services, particularly during registration periods and key announcements. It aims to improve efficiency on frequently asked questions (FAQ) about classrooms, tuition costs, paperwork, thesis guidance, and more. SiAkif was trained on real university data and deployed on Telegram, which consists of a popular platform among students at the institution (Muna et al., 2025).

AVA (Advising Virtual Assistant) is a chatbot designed to increase information access and academic advising efficiency at a public university in the United States (Lucien & Park, 2024). This chatbot that supplements human advisors, was designed focused on prescriptive advice, such as typical requirements and defined procedures, which allows the technical staff to focus on the personalized support, AVA cannot do. The utilization data show that timely access, including outside of business hours, is a significant advantage (Lucien & Park, 2024). The system was launched via the university's portal while keeping privacy in mind, for example, that no identifiable student data was shared with other parties. The design also recognizes limitations, when questions are not prescriptive or involve judgment, students are directed to have human interactions, with advisors. While the case focuses on prescriptive advice, the authors highlight lessons gained and potential future improvements (Lucien & Park, 2024).

Other case studies include the University of Manitoba Libraries' bespoke chatbot (Xuan, 2025). The goal is to improve the speed and efficiency at which library services and information are delivered. Its knowledge base contains 1177 selected webpages from library websites, FAQs, and subject guides, and the response pipeline reformulates the user's question, performs hybrid retrieval, which is vector similarity plus semantic ranking, and generates a natural-language answer with clickable links and citations (Xuan, 2025).

2.3. Technologies Used in Academic Chatbots

The categorization of chatbots can made in many different ways, which reflect the technological needs and respective improvements that shaped their evolution since the 1960s. Adamopoulou and Moussiades (2020) states a fundamental distinction between rule-based bots, which follow defined patterns and scripts, and AI-based chatbots, which employ machine-learning algorithms and NLP in order to provide and deliver more contextualized responses. This last category is divided into retrieval-based systems, selecting the best response from pre-existing possibilities, and generative-based, generating new responses, usually using deep neural networks (Nuruzzaman & Hussain, 2018). They can also be distinguished by domain, which consist of general-purpose bots covering a wide range of topics, whereas domain-specific bots specialize in a single function (Brandtzaeg & Følstad, 2017). Chatbots can be classified functionally into three types, as informative (data provision), conversational (social engagement), and task oriented. Janssen et al. (2020) propose a taxonomy with 17 dimensions across three perspectives: intelligence (e.g., text understanding, personality processing/adaptive self, socio-emotional behaviour), interaction (e.g., multimodality, interface personification, user-assistance design), and context (e.g., application domain, relation duration, chatbot role, collaboration goal, motivation for use), with all the dimensions capturing technical, emotional, and situational aspects of chatbot design.

According to Anwar et al. (2024), NLP is an area of AI dedicated to the understanding and interpretation of the human language, with recent advances, such as transformer models, large-scale pretraining, transfer learning, and work on bias and ethics, have expanded what educational chatbots can do. In their academic assistance chatbot, NLP enables core capabilities including sarcasm detection with RoBERTa, text summarization with BART (Lewis et al., 2020), spelling and grammar correction with T5 (Raffel et al., 2020), job-offer matching using CountVectorizer with cosine similarity (Pedregosa et al., 2011), and question–answering with bidirectional attention flow (Seo et al., 2018) .

Natural Language Understanding (NLU) is a subset of NLP that extracts context and meaning from user inputs, identifying intent and domain entities to allow the chatbot to respond properly (Adamopoulou & Moussiades, 2020). In academic settings, algorithms may still struggle with informal or abbreviated student language, reducing classification accuracy (Hardi et al., 2022).

The integration of a chatbot into the academic ecosystem is a critical component of its design and functionality (Ula et al., 2023). The chatbot can have access to important academic data, mainly through the institutional repositories, which consist of course materials, assignment, calendar and deadlines, so that it introduces a more contextualized and personalized response and support (Wang et al., 2024). The chatbot can be a proactive tool in the learning environment, especially with these kinds of functions (Mesquita et al., 2025).

2.4. Factors Shaping Academic Chatbot Impact

According to Pi and Majid (2020), the development an academic chatbot for a university website requires that essential components are established, such as the bot's type, character or role, content scope, and methodology, so that it may function as an extension of the website, which enhances interaction and service quality. In parallel, the website's objective should focus on how it is designed, how it defines content categories and target audiences, how it facilitates stakeholders to access various types of information, which enhances navigation and findability (Resmini & Rosati, 2011).

A survey involving 207 university students from two higher education institutions in the United Arab Emirates, investigated acceptance of an academic advising chatbot (Bilquise et al., 2024). The findings indicated that Perceived Ease of Use (PEOU) and Social Influence significantly enhanced Behavioural Intention (BI), while Perceived Usefulness (PU), Trust, and Autonomy had no significant effects. Anthropomorphism was marginal at the 0.10 level. The authors view advising chatbots as supplementary to human advisors, providing rapid, all day information access while acknowledging limitations that still require human assistance (Bilquise et al., 2024).

Hardi et al. (2022) evaluates an academic chatbot through user perception on reliability and response quality, and not just because of the technological architecture alone. A user survey yielded over 85% positive ratings for core service attributes such as ability, consistency, responsiveness, and overall performance. The measurement instrument also showed good internal consistency (Cronbach's $\alpha = 0.82$), indicating that the system met expectations for reliable assistance with routine academic queries. At the same time, the study reveals a practical limitation with immediate implications for real-world deployments: accuracy suffers when the chatbot encounters informal or abbreviated student language, indicating that coverage of colloquialisms and non-standard forms remains a weakness even when headline satisfaction appears high. When viewed holistically, the findings paint a balanced picture, which is that the bot showed strong acceptance by its users on core attributes, but the overall classification accuracy can be interpreted as modest, which degrades with informal or abbreviated language.

One of the major worries when using academic chatbots is privacy and data security (Gumusel, 2025). Davar et al. (2025) mention these systems facilitate access to student records and institutional services, and when on attack or misconfiguration might allow unauthorized access, resulting in data breaches that reveal personally identifiable information and academic data. When chatbots are combined with learning management systems, the resulting architecture expands the attack surface and operational complexity, forcing institutions to secure interfaces and data management (Pimentel et al., 2025). Controls that are recommended to ensure privacy and security in academic chatbots are an important concern within students, who express apprehension about data privacy, ethical use and the potential risks of chatbot integration in higher education institutions (Stöhr et al., 2024).

Table 2.1. Factors identified in the literature that impact the perceived effectiveness of academic chatbots

Dimension	Factors	Reference
Positive	Clarity of informative contente, interaction pattern with users and integration into institutional objectives, functioning as an extension of the website	Sau Pi and Abdul Majid (2020)
Positive	Ease of use, trust conveyed and user-centered design. There is also a reduction of administrative workload	Bilquise, Ibrahim, and Salhieh, (2024)
Negative	Replacing human contact, functioning only as complementary support	Bilquise, Ibrahim, and Salhieh, (2024)
Positive	Security, as students perceive the chatbot has a tool without emotional connection or human judgment	Hardi et al. (2022)
Negative	Risk of information leakage through violation of GDPR standards and misuse of user data	Davar et al. (2025)

2.5. Challenges in Chatbot usage

The complexity and variety of user queries pose a significant problem for academic chatbots, making it difficult to correctly grasp both context and meaning (Labadze et al., 2023). Prior research has shown that typical N-gram approaches suffer from data sparsity and very high-dimensional vectors, which limit meaningful intent identification, thus, effective systems rely on appropriate, representative conversational data derived from genuine student contacts (Alias et al., 2019).

Common obstacles in chatbot development are most related to technical aspects, particularly training and tuning NLU models to distinguish intentions and entities with accuracy (Davar et al., 2025). Developers also encounter a continuous lack of real, end-to-end guidance, such as clear tutorials, functioning examples and best practices, which leads to trial-and-error processes and, in public forums, a large proportion of unanswered inquiries on basic issues (Abdellatif et al., 2020). These issues exacerbate one another, when documentation is thin and examples are scarce, novices struggle to build pipelines, wire components together, and detect faults, which slows learning and undermines trust (Abdellatif et al., 2020). As a result, there is a great demand for better support tools, more accessible interfaces, and work simplification to decrease the entry barrier and increase the reliability of what is developed (Abdellatif et al., 2020).

2.6. Technology Acceptance Model and Value-based Adoption Model

TAM is a popular and influential theoretical paradigm for explaining and predicting user acceptance of new technologies (Sohn & Kwon, 2020). Davis (1985) developed the model based on the Theory of Reasoned Action and the model was created expressly to increase understanding of user acceptability of information systems (Sohn & Kwon, 2020). It is regarded as robust, with considerable empirical backing verifying its applicability, so TAM is based on the notion that the perceived benefits of utilizing a technology influence its effective adoption (Kim et al., 2014).

TAM is based on two key perceptual factors which regard the target technology. Perceived Usefulness (PU) is the degree to which a person believes that utilizing a specific system will improve their performance (Davis, 1985). In the literature, specifically in the adoption context, usefulness is frequently assessed as the overall value that a user perceives while adopting a new technology (Kim et al., 2014). In the TAM context, Perceived Usefulness corresponds to the anticipation of outcomes resulting from adoption behavior (Liao et al., 2022). Therefore, PU is a significant TAM aspect that has a direct impact on technology adoption, and empirical research has demonstrated that PU positively influences intention to embrace mobile technologies such as mobile Internet (Kim et al., 2007). PEOU definition consists at what is the degree to which a person believes that using a particular system would be free of effort (Davis, 1989). PEOU has long been recognized as a crucial element influencing technology adoption (Kim et al., 2014), capturing how simple a system is to use and learn. In e-learning systems, PU reflects the user perception of how technology helps them improve and obtain great benefits, and PEOU is viewed has the easier the system to use, the better its perceived utility (Liao et al., 2022).

In its original formulation, TAM contends that both PU and PEOU alter the user's attitude toward the activity, which determines Behavioral Intention (BI) to use. A subsequent version of TAM, however, posits that PU and PEOU have favorable direct positive effects on BI without including attitude. This streamlined variant is considered robust even without the attitude component (Pal et al., 2020).

Technology intention and adoption is frequently explained by TAM. Some examples of its use are intelligent healthcare systems (Lee et al., 2025), Internet-based intelligent systems (Lim & Zhang, 2022) and Web 3.0/metaverse (Shin & Jo, 2024), learning environments and next-generation educational services (Naidoo, 2023), covering teachers' digital technology adoption and the use of artificial intelligence in online learning (Hazzan-Bishara et al., 2025), intelligent advertising systems, intelligent robots and wearable devices such as smartwatches (Sohn & Kwon, 2020).

Despite its considerable empirical support and widespread use (King & He, 2006), TAM has limits and does not account for all aspects of technology adoption (Kim et al., 2014). It is mainly focused on PU and PEOU, which can limit its explanatory value for overall adoption behavior (Sohn & Kwon, 2020), and some consider it too minimalistic for forecasting intention (Pal et al., 2020). Recent research suggests that adoption may be strongly influenced by factors other than TAM's traditional components, such as perceived monetary and non-monetary costs and social influence from peers or family, which can be especially important for university students, who are more sensitive to price and social influence than older groups (Kim et al., 2014).

The Value-Based Adoption Model (VAM) is a theoretical framework for predicting the adoption of new technologies (Kim et al., 2007). It is based on the premise that a user's decision to use a technology involves a trade-off between perceived advantages and perceived costs. In general, VAM believes that high costs discourage adoption while large benefits provide greater motivation, defining adoption as an evaluation of "what is received" against "what is given", (Kim et al., 2007). This interpretation is expressly stated in empirical studies that combine VAM and TAM (Liao et al., 2022), where Perceived Value is defined as the user's total assessment of a product or service's utility based on the balance of advantages and sacrifices (Kim et al., 2017).

In VAM, perceived advantages often include usefulness, the expectation that using the system would improve one's performance, and enjoyment, the intrinsic fun or pleasure of using the system, both of which tend to raise PV in digital service (Liao et al., 2022). Perceived sacrifices include costs paid in money, time, or effort, commonly referred to as Perceived Fee, as well as numerous frictions such as complexity or technicality, which, along with worries about privacy risk, can reduce PV in consumer tech decisions (Kim et al., 2017).

Integrating VAM with TAM improves explanatory power since TAM's two classic beliefs, PU and PEOU, do not necessarily capture the consumer trade-offs that influence adoption outside of organizational settings (Kim et al., 2014). Applied studies have demonstrated how the TAM and VAM integrated model perspective works across disciplines (Liao et al., 2022; Nguyen et al., 2023). Perceived Value (PV) in smart-home IoT services is shaped by both benefits (e.g., utility and enjoyment) and sacrifices (e.g., privacy hazards and resistance to innovation), and this PV influences desire to accept the service (Kim et al., 2017). In the pandemic era, e-learning with Google Meets, a hybrid model that combined TAM and VAM, discovered support for TAM beliefs alongside VAM's benefit components, demonstrating that affective and value appraisals can work together to explain intentions under uncertainty (Al-Maroof et al., 2021). Broader e-learning study utilizing a unified TAM-VAM model also finds that Perceived Value and Attitude are important, with risk perceptions eroding value and perceived charge not always serving as a substantial barrier in this context (Liao et al., 2022).

Through the assessing of models for evolving consumer technology (Sohn & Kwon, 2020), VAM's hedonic route is frequently emphasized (Kim et al., 2007; Liao et al., 2022). Enjoyment has been regular emerging as the strongest predictor of purchase or usage intention, in studies related to AI intelligent products, by demonstrating how the focus on value and consumer-centric models surpass purely utilitarian accounts (Sohn & Kwon, 2020). Research on voice assistants indicate models incorporating value and hedonic dimensions, such as the VAM, are a better way to describe intention than models with the sole focus on utility and ease of use (TAM), suggesting to use the VAM for evolving technologies (Pal et al., 2020).

The same tendency is seen in subscription video-on-demand. In a study based in Mexico, PV was the strongest driver of continued use, with enjoyment and PU boosting value and PEOU having little contribution regarding PV. These findings align with a TAM-VAM synthesis for ongoing digital service adoption (Müller-Pérez et al., 2025). Overall, these findings point to a practical core insight, which combines TAM's belief structure with VAM's cost-benefit calculus and provides a more complete, consumer-realistic account of adoption for modern, often hedonic-leaning technologies, while still acknowledging TAM's original foundational role of PU (Lee et al., 2025; Adnan et al., 2025).

In consumer like circumstances, both the TAM route via Attitude and the VAM route via PV reliably explain BI (Liao et al., 2022). Beyond utilitarian views, perceived enjoyment boosts attitude and directly increases intention, emphasizing the importance of hedonic assessments alongside usefulness in integrated models (Nguyen et al., 2023). In addition, hybrid TAM-VAM research conducted during the pandemic era demonstrates that adding value constructs such as Perceived Technicality and PE to TAM's ease and usefulness improves explanatory power for Intention, indicating that both cognitive beliefs and value or affect are required to account for adoption under uncertainty (Al-Maroof et al., 2021). Table 2.2. shows the various dimensions of TAM, VAM and integrated TAM and VAM models, presented by previous research.

Table 2.2. Dimensions of the TAM, VAM and integrated TAM-VAM models

Model	Dimension	What it captures	Key links	Source
TAM	PEOU	Belief that the system is free of effort to use	PEOU → PU	Davis (1985)
TAM	PU	Belief that using the system improves performance	PU → ATT	
TAM	ATT	Overall positive or negative evaluation of using the system	ATT → BI	
VAM	PV	Overall benefits or sacrifices appraisal	PV → BI	Kim et al. (2017)
VAM	PE	Intrinsic fun/pleasure of using the system	PE → PV	
VAM	Perceived Fee	Monetary and time costs	PF → PV	
VAM	Perceived Technicality	Complexity or technical burden	PT → PV	
VAM	PR	Privacy, security or uncertainty concerns	PR → PV	
Integrated VAM - TAM	BI	Common outcome in the integrated model	ATT → BI and PV → BI	Liao et al. (2022)
Integrated VAM - TAM	Purchase Intention	Outcome used in consumer-product settings	PV / PE / PU → PI	Sohn & Kwon (2020)
Integrated VAM - TAM	Actual Use	Final behavioural outcome (retained from TAM)	BI → Actual Use	Davis (1985)
Integrated VAM - TAM	Continued-Use Intention	Outcome used in ongoing digital services	PV → CI	Müller-Pérez et al. (2025)

TAM is widely used to explain technology adoption in education (Lee et al., 2025; Al-Abdullatif, 2023), with research repeatedly demonstrating its efficacy. Ayanwale and Ndlovu (2024) identified that, in the adoption of academic chatbots in Lesotho, compatibility with students established learning methods and trust in the chatbots system were critical factors affecting BI, in addition to PU and PEOU. Huang and Mizumoto (2024) combined the TAM with the L2 Motivational Self System in the use of ChatGPT for English writing activities, demonstrating that motivational beliefs affected Attitude Towards Use (ATT) and mediated the impact of TAM elements on intention. Taken together, these additions indicate that the TAM is flexible in accommodating new educational technologies by integrating contextual elements like trust, motivation and compatibility, which are especially pertinent in the evolving digital learning landscape (Lee et al., 2025; Galimova et al., 2024).

Parallelly to TAM, the VAM has provided complementary knowledge by capturing the trade-off between advantages and disadvantages in the process of evaluating technology (Kim et al., 2007; Liao et al., 2022). Within this approach, PV functions as a mediator, synthesizing both hedonic advantages, exemplified by PE and detriments, represented by Perceived Risk (PR) (Liao et al., 2022). There are studies that substantiate this balance in educational contexts, like Liao et al. (2022), that shown PE enhanced and PR reduced, PV in learning adoption, thereby influencing students' attitudes and intentions. More recently, Wei et al. (2025) emphasized the significance of PV in the context of technology adoption, demonstrating that value judgments are critical even in areas beyond education, with clear consequences for learning technologies. Ayanwale and Ndlovu (2024) discovered in a chatbot study, that although trust diminishes PR, concerns over privacy and accuracy substantially undermined PV, highlighting PR as a predominantly external obstacle to adoption. These findings are aligned with Kim et al. (2007), who argue that adoption decisions depend on the balance it is perceived to exist between benefits and risks.

2.7. Future Trends and Opportunities

The future of AI assisted in the academic context predicts considerable changes not only in teaching methods but also throughout the ecosystem, including academic services (Labadze et al., 2023). According to Davar et al. (2025), educational chatbots are transitioning from reactive support tools to proactive pedagogical agents. In parallel, integrating learning analytics supports the assessment of learning outcomes and data-informed curriculum and teaching decisions, helping instructors act on evidence to improve courses (Hernández-Campos et al., 2025). This advancement positions chatbots as strategic components of institutional management, capable of providing proactive and personalized support through predicting demands based on each student's past. The chatbot transitions from a basic response mechanism to an intelligent mediator capable of informing students about enrollment renewal deadlines, pending graduation requirements, and foreign mobility options (Davar et al., 2025).

Chang et al. (2023) propose that educational chatbots should progress from only reactive responders to bidirectional, proactive self-regulated learning (SRL) aids, which can assist students with goal formulation, self-assessment, feedback and customization in their academic journey. They specifically recommend implementing reverse prompting, which consists of chatbots offering leading questions to encourage reflection and monitoring, allowing learners to plan goals, evaluate comprehension, and measure progress rather than simply receiving responses.

2.8. Hypothesis Development and Conceptual Model

This subchapter presents the hypotheses formulated based on the literature, theory and the proposed conceptual model. The model is composed of constructs from both the TAM and the VAM. A total of 10 hypotheses were formulated, as on the Table 2.4., to examine how variables such as PEOU, PE, PR, PV, and PU influence ATT and BI of chatbots for academic services.

In the TAM, Davis (1989) established that PEOU positively impacts PU, since technologies that are more straightforward and intuitive are often viewed as more effective by the consumers. Venkatesh and Bala (2008) further asserted that diminishing cognitive effort enhances perceptions of utility. Recent TAM related studies in educational contexts have validated this connection, demonstrating that ease of use is a key predictor of usefulness in systems like academic chatbots (Al-Abdullatif, 2023). Thus, the following hypothesis is formulated:

Hypothesis 1 (H1): PEOU has a positive effect on PU of an academic chatbot.

PU is an essential variable in the TAM and has continually been recognized as a determinant of usage attitude. Davis (1985) and Venkatesh and Bala (2008) assert that when consumers believe a technology improves their performance, they cultivate positive ATT. A study conducted by Schepers and Wetzels (2007) confirmed that PU is one of the strongest predictors of attitude. Therefore, the following hypothesis is formulated:

Hypothesis 2 (H2): PU has a positive effect on ATT of an academic chatbot.

Davis (1989) identified attitude as a crucial mediator in the TAM between beliefs and BI. A subsequent study has been able to validate this association, Liébana-Cabanillas et al. (2018) illustrated in the field of mobile payments that favorable sentiments substantially enhance adoption intentions. A study within the framework of academic chatbots affirms that ATT is one of the most significant determinants of intention to use (Al-Abdullatif, 2023). Accordingly, the following hypothesis is proposed:

Hypothesis 3 (H3): ATT has a positive effect on BI to use an academic chatbot.

The VAM asserts that hedonic factors, such as enjoyment, significantly influence the assessment of value (Kim et al., 2007). In digital services and e-learning contexts, enjoyment has been demonstrated to enhance users' assessment of the overall value of technology (Liao et al., 2022). Thus, the following hypothesis is proposed:

Hypothesis 4 (H4): PE has a positive effect on PV to an academic chatbot.

The literature identifies PR as a major impediment to technology adoption, directly diminishing perceived benefit (Sirdeshmukh et al., 2002). In the VAM, risks like uncertainty, privacy and security concerns are identified as elements that adversely affect value evaluations (Kim et al., 2017). Recent research in educational and AI domains has corroborated this finding, indicating that risks associated with data privacy and system accuracy diminish PV (Davar et al., 2025). Hence, it is proposed the following hypothesis:

Hypothesis 5 (H5): PR has a negative effect on PV of an academic chatbot.

PV integrates cognitive, emotive and risk related aspects, and is regarded as a fundamental factor influencing attitude within the VAM (Kim et al., 2007). Studies in e-learning, like Liao et al. (2022) have shown that elevated value judgments substantially enhance positive attitudes. Müller-Pérez et al. (2025) established that in the digital services era, PV is a strong predictor of user attitudes. In the scope of academic chatbots, students who perceive greater worth are anticipated to cultivate more positive attitudes toward their use. On this basis, the following hypothesis is formulated:

Hypothesis 6 (H6): PV has a positive effect on ATT of an academic chatbot.

The combined effect of TAM and VAM has demonstrated that PV directly predicts BI (Kim et al., 2017). Sohn and Kwon (2020) highlighted that value is essential in the adoption of AI technologies, as users evaluate advantages against sacrifices. Al-Maroof et al. (2021) discovered that the PV of digital technologies, like Google Meets, substantially affected the intention to use them. Accordingly, the following hypothesis is advanced:

Hypothesis 7 (H7): PV has a positive effect on BI to use an academic chatbot.

According to Davis (1989), in addition to influencing usefulness, ease of use also directly influences users' attitudes toward technology. Subsequent modifications of the TAM, notably by Venkatesh and Bala (2008), validated that more intuitive systems foster more favorable sentiments. In academic contexts, Al-Abdullatif (2023) established that PEOU positively influences students' perceptions toward chatbots. Therefore, the following hypothesis is proposed:

Hypothesis 8 (H8): PEOU has a positive effect on ATT of an academic chatbot.

PU is acknowledged as a fundamental factor influencing BI in the TAM (Davis, 1989). A study by Schepers and Wetzels (2007), validated the consistency of this association across several technologies. Al-Maroof et al. (2021) indicated that PU directly influences the intention to embrace e-learning platforms in the realm of educational technology. Accordingly, the following hypothesis is presented:

Hypothesis 9 (H9): PU has a positive effect on BI to use an academic chatbot.

While predominantly linked to VAM, PE may also directly influence user attitudes, particularly in interactive systems. Davis et al. (1992) established that intrinsic satisfaction in computer usage enhances favorable attitude toward technology. Likewise, Kim et al. (2007) shown that enjoyable experiences augment both perceived value and attitudes for adoption. Thus, the following hypothesis is proposed:

Hypothesis 10 (H10): PE has a positive effect on ATT of an academic chatbot.

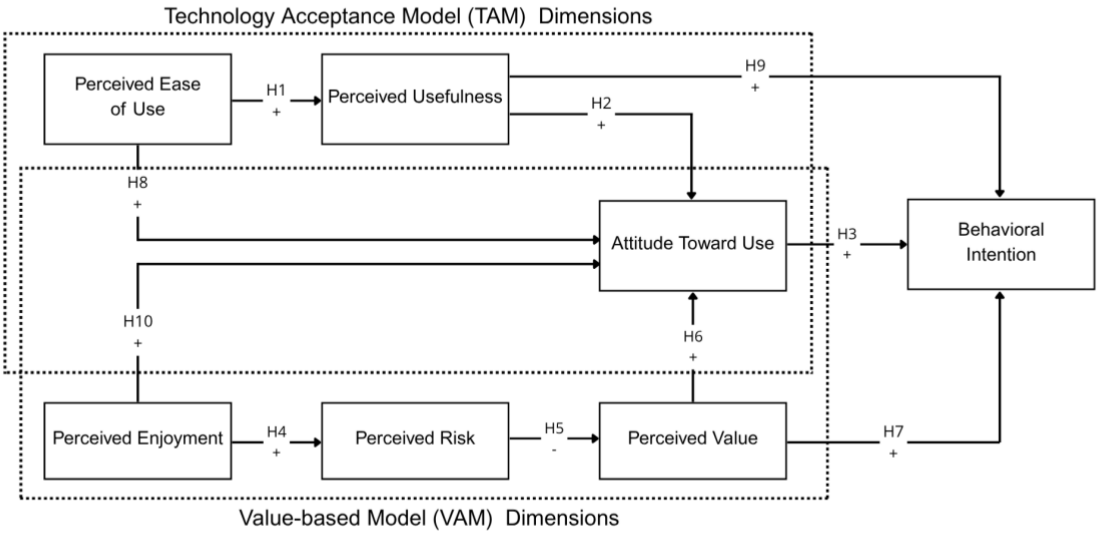

Figure 2.1. Proposed conceptual model

Compared to previously studies, the proposed conceptual model in Figure 2.1 offers a more streamlined and theoretically consistent structure. While a study by Al-Abdullatif (2023), integrated TAM and VAM constructs under a broader "Chatbot Acceptance" outcome, this study focuses on retaining BI as the final dependent variable, in line with classical TAM logic (Davis, 1989).

Table 2.3. Research hypothesis, according to the relationship of TAM and VAM

Expected Relation			Hypothesis
H1	+	TAM	PEOU has a positive effect on PU of an academic chatbot
H2	+	TAM	PU has a positive effect on ATT of an academic chatbot
H3	+	TAM	ATT has a positive effect on BI to use an academic chatbot
H4	+	VAM	PE has a positive effect on PV to an academic chatbot
H5	-	VAM	PR has a negative effect on PV of an academic chatbot
H6	+	Integrated TAM-VAM	PV has a positive effect on ATT of an academic chatbot
H7	+	Integrated TAM-VAM	PV has a positive effect on BI to use an academic chatbot
H8	+	TAM	PEOU has a positive effect on ATT of an academic chatbot
H9	+	TAM	PU has a positive effect on BI to use an academic chatbot
H10	+	Integrated TAM-VAM	PE has a positive effect on ATT of an academic chatbot

In Table 2.3. it is evident the overview of the study hypothesis, and to which model they relate to, namely the TAM, VAM and Integrated TAM and VAM. Besides highlighting the constructs, it is also present the expected positive or negative relations within the model. This structured presentation aims to facilitate the articulation of the research scope and the expected interactions within the constructs, setting the foundation for the empirical study.

CHAPTER 3

3. Methodology

This chapter delineates the methodological framework employed to fulfill the research objectives and empirically evaluate the hypotheses proposed in the conceptual model. The document proceeds to initially outline the research paradigm and methodological framework, highlight its approach. The subsequent sections describe the measures of the constructs, the data collection methodology and the structure of the survey. This chapter also presents the initial descriptive analysis, presenting its techniques, and ensuring the requirements of a quantitative empirical research in technology adoption.

3.1. Research Paradigm

This study adopts a positivist research paradigm (Straub et al., 2004), suggesting that social phenomena may be objectively seen and quantified using empirical data. The positivist approach is compatible for information systems research as it prioritizes hypothesis testing and statistical validation of theoretical models (Orlikowski & Baroudi, 1991).

Aligned with this paradigm, the research employs a quantitative methodology (Gefen et al., 2000). A quantitative approach is suitable for measuring correlations among specified characteristics (Gefen et al., 2000), such as PU, PEOU, PE, PR, PV, ATT and BI, which are fundamental to models like TAM and VAM (Davis, 1989). The overarching strategy is deductive (Hyde, 2000), indicating that hypotheses developed from established theories undergo empirical testing. The deduction strategy is suitable when the objective is to validate or refute theoretical connections rather than to develop theory through qualitative research (Hyde, 2000; (Majchrzak et al., 2000). The study uses a cross-sectional survey methodology (Pinsonneault & Kraemer, 1993), collecting data from respondents at a single unique timeline. It is common to employ cross-sectional designs in technology adoption research as they facilitate the effective collection of perceptions and intentions within a specified group (Venkatesh et al., 2003).

3.2. Measures

The constructs reflect key dimensions of the integrated TAM and VAM framework. Each one of them was measured reflectively, with indicators adapted from previously validated studies in the fields of technology acceptance (Venkatesh & Davis, 2000), e-learning (Liao et al., 2022) and chatbot adoption (Al-Abdullatif, 2023).

Table 3.1. Survey Questionnaire

Constructs	Indicators[1]
PEOU	1. I believe a chatbot for academic services would be easy to use.
	2. Interacting with a chatbot for academic services seems intuitive to me.
	3. I don't think I would need help to use an academic chatbot.
PU	1. I believe an academic chatbot could help me complete administrative tasks more quickly.
	2. A chatbot would make it easier to access information such as deadlines, enrollment, or documents.
	3. Using a chatbot would save me time compared to contacting the university by email or in person.
	4. I think a chatbot would be useful for my academic journey.
PE	1. I imagine that using an academic services chatbot would be enjoyable.
	2. I believe a chatbot would make academic processes less stressful.
	3. Using a chatbot might make university communication feel more relaxed and informal.
PR	1. I have concerns about safety when using a chatbot for academic services.
	2. I worry that a chatbot for academic services might provide incorrect information.
	3. I'm unsure whether a chatbot for academic services would handle my information confidentially.
	4. I wouldn't feel entirely comfortable sharing personal data with a university chatbot.
ATT	1. I have a positive attitude toward the idea of using an academic services chatbot.
	2. I believe chatbots can improve university services.
	3. I find the idea of using an academic services chatbot appealing.
	4. I am open to using this type of tool in the future.
PV	1. I believe the benefits of using a chatbot for academic services would outweigh the risks.
	2. Using a chatbot for academic services would be worthwhile due to the time and effort it could save.
	3. A chatbot for academic services would be a valuable tool for students like me.
BI	1. I would be willing to use an academic services chatbot if my university made one available.
	2. I would like to try using a chatbot for academic or administrative support.
	3. I would recommend this kind of service if I had a good experience with it.
	4. I am open to replacing some in-person or email interactions with a chatbot.

[1] Response format: 5-point Likert scale (1. Strongly disagree, 2. Disagree, 3. Neither Agree or Disagree, 4. Agree, 5. Strongly Agree)

The PEOU construct was evaluated using three items derived from Davis (1989), determining if the chatbot is easy to use, intuitive and does not require external assistance regarding its use. Similar items have been employed in studies of chatbot and e-learning adoption (Al-Abdullatif, 2023). PU included four items reflecting efficiency, time saving and task completion, derived from Davis (1989) and Venkatesh & Davis (2000). Similar metrics were employed in educational technology research (Liao et al., 2022). PE was assessed by three items intrinsic to enjoyment during interactions with chatbots. These were derived from Davis et al. (1992) and Kim et al. (2007), who identified enjoyment as a crucial factor in VAM. PR consisted of four items related to safety, accuracy and confidentiality. This is adapted from conceptualizations of risk by Sirdeshmukh et al. (2002) and Kim et al. (2007). PV was assessed by using three items that emphasized benefits in relation to risks, worthiness of adoption and overall value for students. These items align with the VAM scale established by Kim et al. (2007) and its subsequent adjustments in educational settings (Liao et al., 2022). ATT was assessed using four items that reflect improvement, attractiveness and willingness to utilize. The items were derived from Davis (1989) and utilized in recent educational adoption research (Al-Maroof et al., 2021). BI included four items capturing willingness, trial interest, recommendation and substitution of current interactions. These items were derived from Davis (1989).

This study employed a five-point Likert scale ranging from "1. Strongly Disagree" to "5. Strongly Agree", in accordance with previous chatbot TAM and VAM research (Al-Abdullatif, 2023), as well as methodological guidance that Likert-type scales can be treated as approximately interval when the categories are symmetric and equidistant, suggesting a five- or seven-point Likert formats (Hair et al., 2017).

3.3. Data Collection Procedure

Data were gathered by an online questionnaire provided through the Qualtrics XM platform. This platform was selected due to its capacity in the data collection field, of being efficient and flexible, ensuring data quality and methodological reliability (Miller et al., 2020). The instrument was elaborated with caution so that it guarantees clarity, consistency, and conformity with the constructs and indicators established in the study research model. The survey was conducted from 28th of July to 4th of August of 2025, targeting students enrolled in Portuguese higher education institutions across several academic cycles to improve the relevance and generalizability of the results and collected 182 responses. A convenience sample method was utilized, distributing the questionnaire using social media and messaging platforms to engage a wider range of population. The participation in this questionnaire was limited to people currently enrolled in a Portuguese higher education institution and that simultaneously had sufficient knowledge of the English language to comprehend and complete the questionnaire. Ethical standards were meticulously observed, with participants confirming informed consent, their involvement was completely voluntary, and stringent confidentiality of responses was ensured.

3.4. Data Collection Instrument

The empirical study used primary data gathered through the online questionnaire, in the English language. In the instruments design, significant emphasis was placed on utilizing clear, symmetric and clearly labelled Likert anchors to reduce the likelihood of misinterpretation by the students (Hair et al., 2017). The questionnaire was modified from validated items utilized in previous studies on the TAM and VAM, like Al-Abdullatif (2023) and Venkatesh and Bala (2008) research survey. Prior to the final distribution of the questionnaire, a pre-test was administered to a select group of students to assess the clarity, sequence and general coherence of the questions (Straub et al., 2004). The group of students was selected to have a variety of demographic characteristics. Responding to the students' feedback, there were small modifications placed in the questionnaire, including the refinement of phrasing in certain items and the reordering of questions to enhance coherence.

The questionnaire was separated into two sections, the first being about the demographic information of the participants, composed by closed nominal, ordinal and quantitative scales, and the second section represented the model's constructs. The division between the two sections are important to enable participants to focus on each dimension, as they differ, while it provides item redundancy and improves the items' reliability and validity.

3.5. Data Analysis Techniques

The data analysis was performed in two phases. After its extraction from the Qualtrics platform, the dataset was analyzed utilizing IBM SPSS Statistics 29 and 30. SPSS Statistics was used for data screening and conducting descriptive and inferential statistics to characterize the sample based on gender, age, field of study and previous use of chatbots for academic services.

On the first phase, an independent samples t-test was performed to investigate the impact of gender on students views of chatbots. This test is appropriate for when comparing mean scores between two independent groups (Ruxton, 2006). Responses categorized as "Other / Prefer not to say" were omitted from this comparison due to their minimal representation within the sample, as extremely small subgroups undermine the reliability of statistical comparisons and inflate the risk of Type I and II errors (Blanca et al., 2017). A one-way ANOVA was also conducted for Field of Study, which is appropriate when comparing three or more groups, while the Shapiro-Wilk tests normality (Sureiman & Mangera, 2020). Homogeneity of variances was first assessed with Levene's test (Katsileros et al., 2024). For post-hoc comparisons, Scheffé method was used when homogeneity was maintained, because it permits testing all possible contrasts. On the other hand, the Mann-Whitney U test was used when normality assumptions were violated. When variances were unequal and sample sizes differed, the Games-Howell procedure was applied, as it is specifically tailored for heteroscedasticity with unequal n (Agbangba et al., 2024).

In the second phase, the data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), with the SmartPLS 4 software, which uses a user-friendly environment for model estimation and validation (Hair et al., 2019). PLS-SEM is a variance-based structural equational modeling method that has gained prominence in information systems, marketing and management research, especially when emphasizing prediction and theory building above theory confirmation (Hair et al., 2019). In contrast to covariance-based SEM (CB-SEM), which emphasizes model fit and typically necessitates large sample size and multivariate normality, PLS-SEM demonstrates resilience in scenarios where these prerequisites are not satisfied and is particularly appropriate for models encompassing multiple latent constructs and intricate relationships (Henseler et al., 2009).

This method is particularly pertinent in technology adoption research, where scholars often investigate integrated frameworks like TAM and VAM, which incorporate cognitive (PU and PEOU) and emotive elements (PV, PE and PR) (Al-Abdullatif, 2023). Previous research indicate that PLS-SEM is beneficial when its primary objective is to maximize the explained variance and is assessed by predictive relevance of endogenous dimensions, including ATT and BI (Hair et al., 2019). Additionally, PLS-SEM has been widely used in information systems research because it has the capacity to concurrently evaluate measurement validity, like indicator reliability and discriminant validity, and also test structural hypothesis within a unified modeling framework (Urbach & Ahlemann, 2010).

Recent studies affirm the importance of examining intention to adopt in higher education and digital technology. For instance, Al-Maroof et al. (2021) employed PLS-SEM to examine students' acceptance of Google Meets in a remote learning environment, whilst Al-Abdullatif

(2023) applied it to model students' opinions of chatbots in the educational context. These examples illustrate that PLS-SEM is widely recognized as an appropriate and robust tool in current research on digital learning environments and technology adoption. PLS-SEM delivers the methodological rigor that is necessary to evaluate the integrated TAM and VAM in this investigation, while also providing the flexibility to adapt to the sample characteristics and predictive focus of the research.

Aligned with Hair et al. (2017), the PLS-SEM algorithm in SmartPLS was configured in accordance with the recommended settings. Since all constructs in this study are reflective, the path weighting scheme was selected as the most suitable weighting approach. The initial weights for the outer measurement models were set at +1, ensuring consistent starting conditions for the iterative procedure. The convergence and numerical precision were ensured by establishing a stop criterion at 10^{-7}. The maximum number of iterations used was 300, which is above the minimum barrier required for reliable and replicable outcomes. According to these recommended parameters, it is ensured that the estimation of the TAM and VAM integrated model in SmartPLS is aligned with accepted procedures in PLS-SEM research and affirms the robustness of the results.

A bootstrapping approach with 5000 samples was used to assess the statistical significance of the structural correlations, as recommended by Hair et al. (2017). This non-parametric resampling technique facilitates the estimate of standard errors, t-values and p-values without requiring the data to meet strict assumptions of multivariate normality, rendering it especially appropriate for research in social sciences and education. Bootstrapping was utilized to evaluate the route coefficients among constructs and to determine the reliability of outer loadings in the measurement model. This resampling technique guarantees robust inferences regarding the hypothesized relationships in the integrated TAM and VAM model, providing stable significance estimates despite moderate sample sizes.

The standardized outer loadings are a critical component for assessing the reliability and validity of each construct in the evaluation process of the conceptual model. The internal consistency of each construct was evaluated using Cronbach's Alpha and Composite Reliability (CR). According to Hair et al. (2019), while Cronbach's Alpha is a more traditional measurement of reliability it tends to underestimate internal consistency, especially when constructs have a small number of indicators. Therefore, CR is generally preferred, as it considers the individual loadings of the indicators and provides a more accurate estimate. It is calculated using the following formula, where λ_i represents the standardized outer loading of each indicator (Henseler et al., 2009):

$$CR = \frac{(\sum\lambda_i)^2}{(\sum\lambda_i)^2 + \sum(1 - \lambda_i^2)} \quad (1)$$

Convergent validity was further assessed using the Average Variance Extracted (AVE), which measures the proportion of variance in the indicators explained by the construct relative to the variance due to measurement error (Henseler et al., 2009). It is calculated using the following formula, where λ_i represents the standardized outer loading of each item, and n is the number of items (Henseler et al., 2009):

$$AVE = \frac{\sum \lambda_i^2}{n} \quad (2)$$

According to Hair et al. (2019), an AVE value of 0.50 or above is an indicator that the construct explains more than half of the variance in its observed variables.

Discriminant validity refers to the extent to which a construct is truly distinct from other constructs, both in the conceptual and empirical view (Hair et al., 2019). It is an essential aspect of construct validity, ensuring that a latent variable captures unique variance not accounted for by other variables in the model (Hair et al., 2019). In the absence of discriminant validity, it is unclear whether constructs are measuring different concepts or even the same dimensions (Henseler et al., 2009). One of the most widely used methods for assessing discriminant validity is the Fornell-Larcker criteria, which states that the square root of the AVE for each construct should exceed its highest correlation with every other construct in the model (Fornell & Larcker, 1981).

Due to Fornell-Larcker criteria limited sensitiveness in identifying discriminant validity concerns, Henseler et al. (2015) recommend for the heterotrait-monotrait ratio (HTMT) as a more reliable method. The HTMT assesses the ratio of average correlations between constructs to those within constructs, with results below 0.85, as conservative, or 0.90, as exploratory, typically signifying adequate discriminant validity.

Hair et al. (2019) define the standardized path coefficient (β) as the intensity and direction of a relationship between constructs. Higher absolute values indicate stronger effects. The Standard Error (SE) is a measure of the estimated coefficient's precision produced through the bootstrapping processes, and the t-value is calculated by dividing the estimated coefficient by its SE, so it reflects how many SE's the estimate deviates from zero (Hair et al., 2019). The p-value is calculated from the t-value and used to determine whether the association is statistically significant (Hair et al., 2017).

CHAPTER 4

4. Results

The results chapter presents the empirical findings of the research. Initially, it provides data screening, sample characteristics, descriptive and inferential statistics. Subsequently it evaluates the measurement quality of the constructs and reports the hypothesis tests among the model variables. The explanatory power of the model is also assessed. The chapter concludes with findings for the subsequent discussion.

4.1. Participants

The survey initial section focuses on the demographic of the participants, including questions regarding gender, age, academic background and previous use of chatbots for academic purposes. The demographic profile of the sample (n=182) reveals a diverse range of participants.

Table 4.1. Participants Demographic

Demographics	Distribution	n=182
Gender	Male	103 (56.6%)
	Female	76 (41.8%)
	Other / Prefer not to say	3 (1.6%)
Age	< 19	0 (0%)
	19 - 20	18 (9.9%)
	21 - 22	43 (23.6%)
	23 - 24	60 (33%)
	>= 25	61 (33.5%)
Education	1st year	6 (3.3%)
	2nd year	17 (9.3%)
	3rd year or more	39 (21.4%)
	Master's degree	102 (56.1%)
	PhD or Doctoral	14 (7.7%)
	Post - Bachelor	4 (2.2%)
Field of Study	STEM (Science, Technology, Engineering, Mathematics)	80 (44%)
	Health and Life Sciences	12 (6.6%)
	Social Sciences, Humanities, Arts	35 (19.2%)
	Business, Economics and Law	55 (30.2%)
Previous use of chatbot for academic or administrative support	Yes	140 (76.9%)
	No	42 (23.1%)

In terms of gender, according to Table 4.1, the majority identified as male (56.6%). In the context of age distribution, most of participants were aged 25 years old or over (33.5%), followed closely by those between 23 and 24 range (33%). Educational background varied as well, although a significant portion (56%) reported being enrolled in a Master's degree program, while 21.4% were in their third year or above of undergraduate studies. Regarding academic majors, 44% came from STEM fields, 16.5% from Social Sciences and Humanities, 30.2% from Business, Economics, and Lawand 6.6% from Health and Life Sciences. Finally, most respondents (76.9%) had previously used a chatbot with the intention of having academic or administrative support, indicating a relatively high level of familiarity with this technology. The descriptive results for the TAM related indicators suggest that students view academic chatbots as both easy to use and useful. In a 5-point Likert scale, PEOU item values range from 3.60 to 4.09 (Table 4.2), reflecting predominantly favorable evaluations of usability. The third indicator of PEOU (M = 3.60) shows a lower strength value, when it is compared to the others and its standard deviation was also slightly higher, which shows dispersion towards the mean. PU indicators scored consistently high, with the fourth indicator being identified as the strongest.

Table 4.2. TAM indicators descriptive statistics

Construct	Indicator	Mean	Median	SD	Min	Max
PEOU	1	4.09	4.00	0.78	2	5
	2	4.02	4.00	0.78	1	5
	3	3.60	4.00	1.15	1	5
PU	1	4.06	4.00	0.87	1	5
	2	4.17	4.00	0.83	1	5
	3	4.04	4.00	0.86	1	5
	4	4.23	4.00	0.79	1	5

In Table 4.3., the VAM indicators represent students' assessments of enjoyment, risk and overall value. PE items had a moderate score, indicating that students find chatbots relatively entertaining, although not exceedingly enjoyable. PR items had a consistently low average, and its median values suggested more neutral responses on this construct. Elevated averages were also recorded on PV items.

Table 4.3. VAM indicators descriptive statistics

Construct	Indicator	Mean	Median	SD	Min	Max
PE	1	3.87	4.00	0.89	1	5
	2	3.77	4.00	0.95	1	5
	3	3.84	4.00	0.87	1	5
PR	1	2.74	3.00	1.09	1	5
	2	2.95	3.00	1.08	1	5
	3	2.75	3.00	1.11	1	5
	4	2.78	3.00	1.11	1	5
PV	1	4.03	4.00	0.82	1	5
	2	3.99	4.00	0.81	1	5
	3	4.03	4.00	0.83	1	5

The outcome constructs ATT and BI both recorded high average values. ATT indicators varied from 4.13 to 4.27 (Table 4.4.), with the second indicator exhibiting the highest mean. BI indicators exhibited robust performance, although the fourth indicator was slightly lower. The standard deviation values showed low to moderate spread of responses around the mean.

Table 4.4. Integrated TAM and VAM indicators descriptive statistics

Construct	Indicator	Mean	Median	SD	Min	Max
ATT	1	4.21	4.00	0.80	1	5
	2	4.27	4.00	0.77	1	5
	3	4.24	4.00	0.76	1	5
	4	4.13	4.00	0.83	1	5
PU	1	4.15	4.00	0.85	1	5
	2	4.08	4.00	0.84	1	5
	3	4.05	4.00	0.85	1	5
	4	3.94	4.00	0.87	1	5

4.2. Exploratory Comparison

Table 4.5. displays the descriptive data for each construct categorized by Gender, Age and Field of Study, along with the relevant inferential tests.

Table 4.5. Construct Descriptives and Inferential Statistics by Gender, Age and Education

			Gender		**Age**				**Education**			
Construct	**Statistics**	**Total**	Male	Female	19 - 20	21 - 22	23 - 24	Over 25	STEM	Health and Life Sciences	Social Sciences, Humanities and Arts	Business, Economics and Law
			n=103	n=76	n=18	n=43	n=61	n=61	n=80	n=12	n=35	n=55
PEOU	Mean	3.90	3.87	3.91	4.00	4.10	3.85	3.79	3.97	3.72	3.98	3.90
	SD	0.68	0.72	0.70	0.67	0.60	0.64	0.75	0.65	0.51	0.64	0.68
	Statistical Test	-	t=-0.02, p=0.83, d=0.06		H(2) = 4.21, p = .122				F(3.178)=1.76, p=.157, η^2=.03			
PU	Mean	4.11	4.10	3.96	4.17	4.40	4.19	3.82	4.21	4.19	3.69	4.23
	SD	0.70	0.66	0.70	0.59	0.54	0.63	0.69	0.70	0.34	0.76	0.61
	Statistical Test	-	t=-0.08, p=0.94, d=0.02		H(2) = 3.37, p = .185				F(3.178)=5.64, p=.001, η^2=.09 Levene p=.115, Scheffé			
PE	Mean	3.61	3.61	3.58	3.53	3.97	3.66	3.32	3.77	3.47	3.09	3.73
	SD	0.86	0.78	0.82	0.65	0.78	0.79	0.94	0.77	0.48	1.09	0.75
	Statistical Test	-	t=0.2, p=0.84, d=0.04		H(2) = 9.22, p = .010, Mann-Whitney				F(3.178)=6.21, p<.001, η^2=.10 Welch F(3,49.86)=4.37, Games-Howell			
PR	Mean	3.20	3.15	3.24	3.22	3.06	3.12	3.36	3.11	3.17	3.54	3.10
	SD	0.94	0.83	0.85	1.12	0.98	0.97	0.87	0.92	0.91	1.05	0.88
	Statistical Test	-	t=-0.62, p=0.54, d=0.12		H(2) = 0.14, p = .931				F(3.178)=1.99, p=.117, η^2=.03			
ATT	Mean	3.91	3.99	3.78	3.82	4.16	3.98	3.68	4.05	4.06	3.29	4.05
	SD	0.81	0.72	0.74	0.78	0.68	0.79	0.90	0.67	0.48	1.12	0.67
	Statistical Test	-	t=1.76, p=.08, d=.26		H(2) = 2.99, p = .224				F(3.178)=9.20, p<.001, η^2=.13 Welch F(3,47.66)=3.87, Games-Howell			
PV	Mean	3.81	3.91	3.68	3.74	4.08	3.83	3.63	3.96	3.94	3.27	3.92
	SD	0.81	0.68	0.72	0.78	0.70	0.76	0.90	0.73	0.53	1.12	0.57
	Statistical Test	-	t=1.85, p=.07, d=.28		H(2) = 4.39, p = .111				F(3.178)=7.33, p<.001, η^2=.11 Welch F(3,46.30)=3.87 Games-Howell			
BI	Mean	4.01	4.05	3.77	4.07	4.26	4.01	3.82	4.14	4.17	3.43	4.01
	SD	0.75	0.71	0.75	0.70	0.58	0.74	0.84	0.64	0.43	1.03	0.75
	Statistical Test	-	t=0.61, p=0.54, d=.08		H(2) = 3.49, p = .175				F(3.178)=9.96, p<.001, η^2=.14 Welch F(3,47.86)=5.20 Games-Howell			

According to Table 4.5., males exhibited a marginally superior score on ATT (M = 3.99, SD = .72) relative to females (M = 3.78, SD = .74), however, this disparity lacked statistical significance (t (90) = 1.76, p = .081). Likewise, PV was marginally greater in males (M = 3.91, SD = .68) compared to females (M = 3.68, SD = .72), although the difference was not statistically significant (t (90) = 1.85, p = .067). The effect sizes for these variations were minimal, suggesting restricted practical relevance. The findings indicate that attitudes of chatbot acceptance are predominantly uniform across gender categories in this sample.

A one-way ANOVA was utilized to analyze the comparison involving more than two independent groups, on Age and Field of Study. According to conventional statistical thresholds, results with p-values below 0.05 were interpreted as statistically significant, while values above this threshold were considered not significant (Kim, 2015).

Effect sizes are reported to contextualize statistical significance. For the ANOVA's, Eta squared (η^2) was used, adhering to traditional thresholds of 0.01 (small), 0.06 (medium) and 0.14 (large) (Cohen, 1988). In Gender comparisons involving two groups, effects were analyzed alongside the t-tests, utilizing Cohen's d. In this sample, gender revealed no significant differences, and the associated effects were minimal. In the Field of Study, the Levene's test confirmed the assumption of the homogeneity of variances, and the ANOVA tests revealed significance for PU, PE, ATT, PV and BI, although not for PEOU and PR. The most substantial effects were noted for ATT and BI, indicating significant variability in attitude and intention across disciplines. For Age, the 19-20 group did not meet the assumption of normality, as per the Shapiro-Wilk test ($W=.851$, $p < .001$). Therefore, the Kruskal-Wallis non-parametric test was considered for the comparison of the groups. This test revealed significant difference in PE within the Age groups, although there were no other significative differences for the other groups. The Mann-Whitney U post-hoc test demonstrated that the 21-22 group scored significantly higher than the other groups, with statistically significant differences when compared to the 19-20 and >=25 groups, according to Table 4.6.

Across factors with 3 groups or above, post-hoc tests comparisons were elaborated, as presented in Table 4.6. For Age, the Mann-Whitney U post-hoc test demonstrated that the 21-22 group scored significantly higher than the other groups, with statistically significant differences when compared to the 19-20 and >=25 groups, according to Table 4.6.

For field of study, Scheffé was employed when homogeneity was confirmed, and Games-Howells was utilized otherwise. The results, in Table 4.6., indicated a trend wherein Social Sciences, Humanities and Arts (SSH&A) generally had lower scores compared to the other fields. The most significant disparities were observed in ATT and BI, as Health and Life Sciences (H&LS) had a higher score than SSH&A, while both STEM surpassed SSH&A and Business, Economics and Law (BE&L) outperformed SSH&A. In terms of PU, and through Scheffé post-hoc, STEM outperformed SSH&A, and BE&L surpassed SSH&A. On the other hand, PEOU and PR exhibited no significant effect by field of study, so no post-hoc test was conducted.

Table 4.6. Post-hoc results by Age and Field of Study

Dimension	Construct	Post-hoc Test	Most significative pair (ΔM, *p*)	Other significative pairs
Age	PE	Mann-Whitney	21-22 > >=25 (.65, .001)	21-22 > 19-20 (.44, .007)
Field of Study	PU	Scheffé	BE&L > SSH&A (.54, .005)	STEM > SSH&A (.52, .003)
	PE	Games-Howell	STEM > SSH&A (.68, .008)	BEL > SSH&A (.64, .017)
	ATT	Games-Howell	H&LS > SSH&A (.77, .010)	STEM > SSH&A (.76, .003) BEL > SSH&A (.76, .004)
	PV	Games-Howell	STEM > SSH&A (.69, .008)	H&LS > SSH&A (.67, .038) BEL > SSH&A (.65, .014)
	BI	Games-Howell	H&LS > SSH&A (.74, .007)	STEM > SSH&A (.71; .003) BEL > SSH&A (.58; .002)

4.3. Conceptual Model Validation

In evaluating the measurement model, the standardized outer loadings are a critical component for assessing the reliability and validity of each construct. According to Hair et al. (2019), standardized outer loadings should ideally exceed 0.708, from Table 4.7., to indicate that each item strongly contributes to the construct it is intended to measure. In Table 4.7., it is shown that almost every construct meets these criteria, with most of the standardized outer loadings well above the recommended threshold. However, the construct PEOU includes one item with a substantially low standardized outer loading of 0.258. This number suggests that this item does not adequately reflect the construct and may compromise the validity of the measurement. Since the standardized outer loading is below 0.40, it will be removed for further analysis (Hair et al., 2017).

Table 4.7. shows that all constructs in this model meet the required CR level of 0.70 threshold, demonstrating acceptable internal consistency (Hair et al., 2017). The values for all constructs are above the AVE threshold (>50), supporting the convergent validity of the measurement model.

Table 4.7. The analysis of the measurement model[2]

Construct	Indicator	Standardized Outer Loadings	Alpha	CR	AVE
PEOU	1	0.914	0.806 (0.631)	0.919 (0.776)	0.837 (0.580)
	2	0.915			
	3	0.258			
PU	1	0.831	0.820	0.882	0.652
	2	0.812			
	3	0.712			
	4	0.867			
PE	1	0.879	0.796	0.879	0.708
	2	0.888			
	3	0.750			
PR	1	0.853	0.835	0.889	0.668
	2	0.782			
	3	0.830			
	4	0.802			
ATT	1	0.885	0.916	0.941	0.799
	2	0.920			
	3	0.901			
	4	0.869			
PV	1	0.873	0.891	0.933	0.822
	2	0.927			
	3	0.919			
BI	1	0.913	0.847	0.898	0.690
	2	0.891			
	3	0.812			
	4	0.688			

In the current study, according to Table 4.8., discriminant validity was confirmed for these constructs: PEOU, PU, PE, PR, ATT and PV. However, BI did not meet this requirement, suggesting a lack of discriminant validity between BI and ATT, as its correlation value (0.841) was slightly higher than the square root of AVE for BI (0.831).

In Table 4.8., the majority of the constructs met the HTMT thresholds, however, four pairs surpass the recommended value: ATT – BI (0.951), PEOU – PU (0.906), PV – ATT (0.950) and PV – BI (0.912). The results indicate a strong correlation among ATT, BI and PV in this study.

[2] In Table 4.7. values in parenthesis were calculated including the third standardized outer loading of PEOU

Table 4.8. Discriminant validity analysis and correlation matrix[3]

Construct	1	2	3	4	5	6	7
PEOU	**0.915**	0.654 (0.906)	0.576 (0.706)	-0.182 (0.211)	0.655 (0.766)	0.591 (0.699)	0.574 (0.689)
PU	0.654 (0.906)	**0.807**	0.693 (0.830)	-0.238 (0.282)	0.768 (0.841)	0.724 (0.881)	0.720 (0.855)
PE	0.576 (0.706)	0.693 (0.830)	**0.841**	-0.204 (0.239)	0.693 (0.815)	0.698 (0.791)	0.645 (0.763)
PR	-0.182 (0.211)	-0.238 (0.282)	-0.204 (0.239)	**0.818**	-0.369 (0.500)	-0.435 (0.417)	-0.350 (0.413)
ATT	0.655 (0.766)	0.768 (0.841)	0.693 (0.815)	-0.369 (0.500)	**0.894**	0.859 (0.950)	0.848 (0.912)
PV	0.591 (0.699)	0.724 (0.881)	0.698 (0.791)	-0.435 (0.417)	0.859 (0.950)	**0.907**	0.805 (0.912)
BI	0.574 (0.689)	0.720 (0.855)	0.645 (0.763)	-0.350 (0.413)	0.848 (0.912)	0.805 (0.912)	**0.831**

According to Perneger & Combescure (2017), the hypotheses in this investigation were considered supported with p-values less than 0.01 interpreted as moderately significant, and those less than 0.001 designated as highly significant.

The hypothesis testing results show numerous significant correlations within the extended TAM and VAM model. PEOU has a significant positive effect on PU (H1: $\beta = 0.654$; SE = 0.050; t = 13.098; $p < .001$), supporting the TAM core assumption. PU has a significant impact on ATT (H2: $\beta = 0.220$; SE = 0.068; t = 3.254; p = .001), and ATT is the strongest predictor of BI (H3: $\beta = 0.528$; SE = 0.087; t = 6.069; $p < .001$). The VAM extensions show that PE has a positive impact on PV (H4: $\beta = 0.579$; SE = 0.061; t = 9.537; $p < .001$) and PR has a significant negative impact (H5: $\beta = -0.435$; SE = 0.061; t = 7.084; $p < .001$). PV significantly predicts both ATT (H6: $\beta = 0.579$; SE = 0.061; t = 9.537; $p < .001$) and BI (H7: $\beta = 0.260$; SE = 0.094; t = 2.758; p = .006), underlining its role in mediating between emotional aspects and behavioral outcomes. PEOU also has a weaker but still significant influence on ATT (H8: $\beta = 0.137$; SE = 0.061; t = 2.234; p = .026). By contrast, PU does not significantly affect BI (H9: $\beta = 0.127$; SE = 0.070; t = 1.812; p = .070), and PE similarly fails to significantly predict ATT (H10: $\beta = 0.057$; SE = 0.066; t = 0.870; p = .384).

Overall, the results show the hypothesis H1 to H8 were supported, with the exception of H9 and H10, which were not supported.

[3] The bold values represent the square roots of the AVE and the values in parentheses indicate the HTMT ratios

Table 4.9. Results of the hypothesis testing

H	Independent Variables	Dependent Variables	Path Coefficients (β)	Standard Errors (SE)	*t*-values	*p*-values	R^2	R^2 *Adjusted*
H1	PEOU	PU	0.659	0.051	12.950	<.001	0.428	0.425
H2	PU	ATT	0.218	0.068	3.209	<.001	0.795	0.790
H3	ATT	BI	0.528	0.087	6.070	<.001	0.748	0.744
H4	PE	PR	-0.204	0.074	2.743	0.006	0.042	0.036
H5	PR	PV	-0.435	0.061	7.084	<.001	0.190	0.185
H6	PV	ATT	0.579	0.060	9.591	<.001	0.795	0.790
H7	PV	BI	0.260	0.094	2.758	0.006	0.748	0.744
H8	PEOU	ATT	0.139	0.062	2.235	0.025	0.795	0.790
H9	PU	BI	0.127	0.070	1.812	0.070	0.748	0.744
H10	PE	ATT	0.056	0.066	0.849	0.396	0.795	0.790

According to Cohen (1988), the explanatory power of a research model is measured by R^2 value, which represents the variance in the dependent construct that is explained by the independent ones. The interpretation of the R^2 value relies on the classification small if $R^2 < 0.02$, medium if $0.02 < R^2 < 0.26$ and large if $R^2 > 0.26$ (Cohen, 1988). In this study, and according to the Table 4.9., the R^2 for ATT (0.795), BI (0.748), and PU (0.428) shows strong explanatory power for the three constructs, suggesting that the independent variables account for a substantial portion of variance which exists in these constructs. PV (0.190), while lower, almost exceeds the minimal threshold, showing that emotional and risk-related factors capture a relevant share of variance. These findings provide evidence that the integrated TAM–VAM model is effective in explaining students' acceptance of academic chatbots.

According to Hair et al. (2019), adjusted R^2 provides a more conservative estimate of explanatory power and close values between adjusted R^2 and R^2 suggest model stability and reduce the likelihood of overfitting, which applies to the current study. It is interesting to note that the construct PR has a small effect R^2 (0.042) size, indicating that other constructs in the model were unable to explain its variation. Risk perceptions were demonstrated as being mostly an external factor, as PV was significantly impacted negatively.

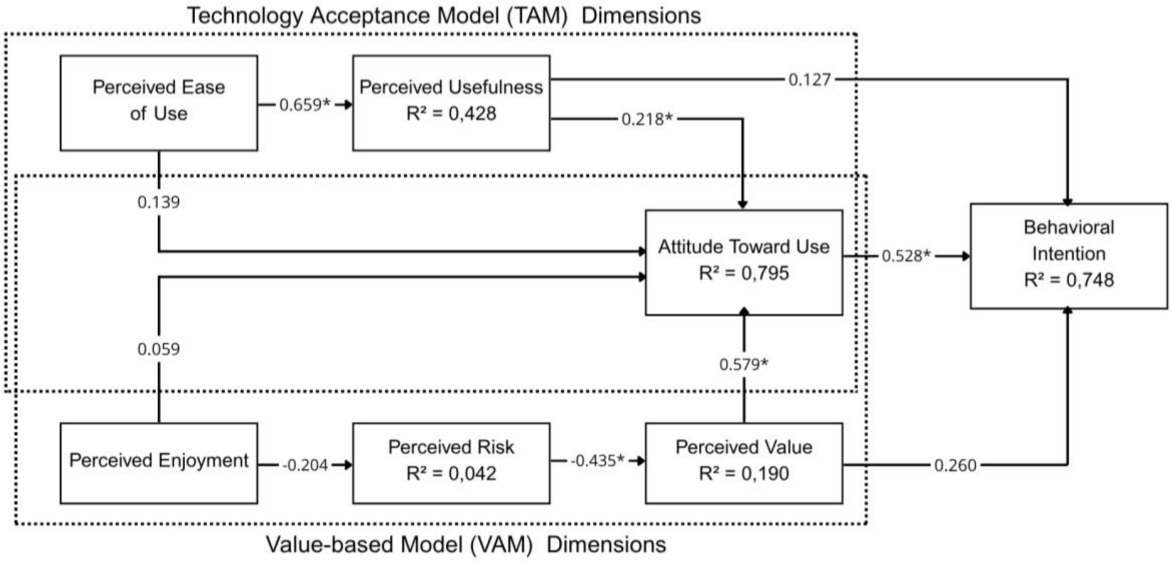

Figure 4.1. Standardized path coefficient results
(highly significant at p-value < 0.001)*

4.4. Discussion

Overall, the study findings reinforce the relevance of TAM constructs while highlighting the complementary role of VAM dimensions such as enjoyment, risk and value in shaping BI. The findings offer crucial information about these frameworks' predictive validity in the context of higher education.

The inferential analysis showed the most significant differences in the perceptions of academic chatbots, mainly on age and field of study groups. The students aged between 21-22 years old demonstrated significantly higher levels of PE, compared to the 19-20 and >=25, which indicates a highlighted stage of university life. The variety of field of study demonstrated that Social Sciences, Humanities and Arts report lower ATT and BI, when compared to STEM, Health and Sciences and Business, Economics and Law, which demonstrates there are fields in which the openness to technology adoption is higher, compared to not so related to technology subjects, like Social Sciences, Humanities and Arts. These results exemplify the way chatbot design must account for the difference fields of study.

Since it was expected, there were routes with weaker or non-significant values, alongside hypothesis that were supported by the model. The statically significant impact of PEOU on PU can be interpreted as a reinforcement of the results that clearly support the robustness of the TAM. This statement is aligned with the original TAM definition by Davis (1985) and its subsequent extensions (Venkatesh & Bala, 2008), which emphasize on how usability enhances the perception of usefulness. In the context of academic chatbots, this implies that students are more likely to view the system as a useful and helpful academic tool if they find it intuitive.

Further supporting the longstanding statement that usefulness influences overall appraisal, PU had a significant positive effect on ATT (Venkatesh & Davis, 2000). These results support the notion that academic technology must provide real benefits in order to be accepted by students.

It's important to note that the association between PEOU and ATT was small but statistically significant, which contrasts with other TAM-based research in education that found that attitudes were more strongly predicted by ease of use (Al-Abdullatif, 2023). There is one explanation that lies in the profile of today's university students, who are often described as being digital natives. According to Hamelmann and Drechsler (2018) digital natives are used to technology, value efficiency and results over usability, and believe that new systems are simpler to use due to past experience. In this situation, usability ceases to be a differentiator and instead becomes a standard requirement. As a result, other factors, specifically PU, have a greater influence on how students feel about academic chatbots.

Addressing VAM, the findings confirm its role in complementing TAM. PR was strongly impacted by PE, supporting (Liao et al., 2022), that hedonic and affective experiences play a role in reducing risk perceptions in online learning adoption. In contrast with research that indicates that enjoyment is directly promoted by positive attitudes (Davis et al., 1992), PE was not a significantly predictor of ATT. This implies that while enjoyment increases value in academic setting, it does not independently lead to positive attitudes. Although they may value engaging features, students ultimately assess chatbots based primarily on their usefulness than because of their hedonistic appeal.

PR had a significant negative impact on PV, supporting earlier research showing that risk perceptions undercut perceived advantages (Sirdeshmukh et al., 2002). PR has a notably low R^2 value (0.042), that suggests other model constructs were unable to explain it. This indicates that risk is mainly an exogenous factor, that is influenced more by general issues like data security, privacy and institutional trust than by characteristics unique to chatbots. Also, it is important to note that PR had a significant impact on PV, in spite of this, serving as a filter that decreases perceived advantages, independently of other advantageous aspects. There is a key aspect to consider, which is that risk managements need to be handled independently of usability and utility. Although chatbots are simple to use and helpful, students can undermine these aspects if accuracy, security and trust and not specifically addressed.

PV played a key role in the model, accurately predicting both ATT and BI. This supports the VAM theory (Kim et al., 2007), which mentions that value serves as a mediator between adoption, risks, and benefits. The construct serving as mediator in this study was PV, which combined the emotional and risk-based assessments of VAM, PE and PR, with the cognitive beliefs of TAM, PU and PEOU. These results demonstrate that students mainly use academic chatbots, not only because they are convenient and practical in use, but also because they balance the advantages of using them against the risks and the enjoyment of using them.

Chatbots in the context of academic services acceptance comprehension is provided through the TAM and VAM integrated model. TAM has a special focus on cognitive evaluations of usefulness and easiness. On the other hand, VAM focuses more on emotional, and risk related factors that affect value perceptions. This study has the capacity to demonstrate how value can serve as a pivotal mediator, that influences attitudes and intentions through perceptions of enjoyment and risk. Practically speaking, the findings show that the highest explanatory power was reached through the integration of both models, with PV acting as a central mediator. This is consistent with other integrated models (Al-Abdullatif, 2023), but it offers more convincing proof that the primary mediating factor in the adoption of academic chatbots is PV.

It is also important to note that discriminant validity analysis indicated that exists significant intersecting among three constructs, ATT, BI and PV, and this suggests that students perceive these dimensions as intimately interconnected within the context of an academic chatbots. Recent empirical investigations have revealed similar results, for instance Wei et al. (2025) identified a substantial correlation between perceived value, attitude and behavioral intention in fintech adoption. Similarly, Tzeng (2011) demonstrates costumers value evaluations are closely linked to their attitudes and intentions toward system usage.

CHAPTER 5

5. Conclusion

This research examined the factors that influence students' acceptance of chatbots for academic services in higher education by integrating two widely recognized theoretical models, the TAM and the VAM. Ten hypotheses that connected dimensions including PEOU, PU, PE, PR, PV, ATT and BI were tested using a quantitative technique with a sample of Portuguese university students. In the results, it is evident the factors that influence chatbot adoption in an academic setting, together with the explanatory efficacy of well-established theories.

The findings confirm three important points. Firstly, TAM is still a reliable paradigm since ATT and BI are significantly influenced by PU indirectly through ATT, and by PEOU both directly and indirectly through usefulness. Secondly, VAM widens its explanatory power, by demonstrating that PV serves as a mediating construct that integrates cognitive, emotional, and risk-related perceptions. Thirdly, the results are evidence that value and risk have unique functions, which means that value is essential in the connection of enjoyment, risk, and usefulness to adopt. On the other hand, risk is an exogenous but important aspect that can reduce perceived advantages.

The combined approach of TAM and VAM models illustrate the advantages of integrating cognitive and value-based frameworks in education technology acceptance research. The current research shows that explanatory models need extend usability and utility to capture the complex trade-offs students make when evaluating new technologies.

The results indicate that PU is a primary factor in students' assessment of chatbots for academic services. The statistically significant correlation between PEOU and PU substantiate the TAM premise (Davis, 1989), that ease of interaction increases perceived utility. In this sense, students typically relate the utility of chatbots with their capacity to conserve time, optimize administrative processes and readily availability on request. This is aligned with previous studies of technology acceptability in educational environments, which indicates that PU is one of the most significant aspects (Al-Abdullatif, 2023; Al-Maroof et al., 2021). Thus, university students regard chatbots as useful and advantageous instruments, contingent upon their ability to enhance efficiency and give academic assistance rather than an inefficient source.

This research demonstrates the PEOU exerts both direct and indirect influences on students' attitudes regarding chatbot adoption. The direct impact on ATT was relatively weak, although significant, whereas PEOU exerted a strong influence on PU, which subsequently affects attitudes.

This illustrates an indirect connection that aligns with the TAM (Venkatesh & Davis, 2000). The results illustrate that students who perceive chatbots as intuitive and user-friendly are more likely to consider them as beneficial and to create positive attitudes towards their use. Students have an expectation that usability is already built-in, since they have greater technical proficiency, so it has a smaller impact on attitudes. Thus, although user-friendliness is a crucial requirement, its influence on attitudes seems to be predominantly mediated by PU and the specific relevance of the system to academic requirements.

The results validate that PV emerges from a combination of emotional and risk-related elements, illustrating the dual impact of rewards and sacrifices as outlined in the VAM (Kim et al., 2007). PE had a significatively positive impact on PV, which aligns with studies that demonstrate that hedonic experiences augment value evaluations in educational technology (Liao et al., 2022). In contrast, PR exerted a significant negative influence on PV, indicating that apprehensions over privacy, reliability, and data veracity considerably diminish students' perception of the value of chatbots. There are built-in aspects that stand out from the specific characteristics of the chatbot itself, mainly risk and security perceptions, which explains the low explanatory power of PR. It was also evident that these risk concerns decrease, when enjoyment increases, which also has enhanced the explanatory power of PV.

It is relevant to note that ATT has emerged as a crucial mediating construct, connecting cognitive, emotional and evaluative perspectives to BI. The results indicate that ATT is a strong predictor of BI, confirming its significance in models of technological adoption. It is important to note, that PV significantly influenced attitude, indicating that student's comprehensive assessment of advantages and disadvantages influences their perceptions of chatbots. The findings suggest that students' attitudes function as the mechanism that transforms evaluations of utility, enjoyments and value into genuine adoption intentions. The strong correlation between ATT, PV and BI indicates that, in academic settings, positive assessments of value and usefulness are closely linked to the willingness to use chatbots.

There are many perceived advantages of the use of chatbots for academic services by the students, which are efficiency, fast and immediate responses and accessibility. The research findings indicated that dimensions like usefulness, ease of use and value have significant positive impact on both attitude and intention, affirming that chatbots are valued when they deliver timely, pertinent and easy assistance for academic assignments.

5.1. Contributions

This study provides empirical contributions for higher education institutions aiming to incorporate chatbots into academic and administrative settings, in addition to its theoretical implications. The findings emphasize that effective adoption mostly relies on the process in which institutions create, execute and express the value of these tools to students. Universities should seek to prioritize the advancement of chatbot systems that are dependable, transparent and authentically advantageous to students' academic pursuits. There are some important aspects to ensure, such as, response precision, reliable performance and transparent data privacy protocols, which are essential for cultivating confidence and acceptance. Higher education institutions should concentrate on the development of chatbots that focus on these aspects, by providing pertinent and significant advantages, such as making bureaucratic procedures more efficient, providing immediate responses to academic questions, or facilitating personalized learning trajectories. Incorporating interactive or engaging features can improve user experience. However, these elements should seek to increase, not replace, the systems functional integrity or reliability.

Additionally, higher education institutions should assign their resources to promote a better image of chatbots, with the use of awareness initiatives that can enhance favorable opinions. This is a complex process, but it can involve showcasing positive use cases and organizing practical workshop sessions, that enhance the positive factors of its use, like the time saving and accessibility advantages. Trust in institutional technology is increased by these activities, and it also enhances students trust in AI-driven. Ultimately, by methodically addressing these factors, institutions could transform chatbots from experimental technology into reliable and useful tools for academic support and engagement.

5.2. Limitations

While this study makes contributions to both theory and practice, it is not without certain limitations. Although the sample of 182 participants is in a theoretical way sufficient for the statistical analysis, it may not be the most accurate reflection of the diversity of the Portuguese student population. It is important to consider the analysis of the results with some caution, since students view of chatbots adoption can be influenced by their characteristics, such as academic fields, study levels or other institutional situations. Additionally, the environment in which the questionnaire was distributed can influence the sample, as it was done using messaging applications and social media, which can had bias by attracting students who are already more used to a tech environment. In this sense, the self-reported questionnaire in it-self, can introduce the risk of bias and also does not account for changes in perception over time. In the questionnaire, it is possible some items were not understood consistently, and had an impact on the accuracy of responses, mainly because it was distributed in the English language, and not in the participations native tongue. For higher education institutions, it is essential, especially in a digital age, to ensure chatbots are dependable, safe and have an impact to students.

From a theoretical standpoint, the model was limited to the TAM, VAM and their integration model constructs, not evolving other potentially pertinent elements that could have been important. The scope of the study is further limited by concentrating on academic chatbots, since adoption patterns may vary for other variations of chatbot applications, such as in different environments. Additionally, the study also interprets volatile concepts such as risk, value, and utility as perceptions that do not change over time, even though these perceptions are likely to change because of increasing experience and familiarity of the students with the technology. Ultimately, external factors might restrict how broadly the results may be applied.

It is important to note that different countries and educational systems can have non-identical results, so we cannot assume the generalizability of them, as they can be impacted by cultural factors that differ from Portuguese students. It is also relevant to note that the timeframe of this study may not reflect accurate results when applied to future contexts, as technology has been evolving at an increasing fast pace. A more in-depth examination of the subjective experiences of the students, which may have been enhanced by qualitative techniques like focus groups or interviews, was also made impossible by the sole use of a quantitative approach.

5.3. Avenues of future research

There are several directions that call for further research, to further elaborate on these limitations. Firstly, it is important to obtain a more representative sample, which means a greater variety of student perceptions, so future research should try to widen the sample base both in Portugal and abroad. The comparison between countries and cultures is an important way to provide a significant perspective about the way institutional, cultural and national contexts differ the perception and adoption of chatbots. In this sense, it would be beneficial for future research to study in a more dynamic view of how acceptance changes as students gain more experience with chatbots, and how more dynamic frameworks monitor perceptions of risks, value and utility over a longer period of time.

A future study has the opportunity to widen the model, with the introduction of more constructs that are integrated in other technology adoption frameworks, such as trust, social influence, environments and prior experience. These constructs can be a factor of improvement in the model's explanatory capacity, by offering a more comprehensive understanding of adoption behavior. Researchers also have the opportunity to distinguish between different types of chatbot applications, such as peer-to-peer platforms or administrative support, as perceived advantages and disadvantages vary depending on the system's scope and purpose.

A combination of quantitative and qualitative methods, which is a mixed methodology strategy, can be a possible avenue for future research. A qualitative approach is also a good opportunity, since it can be a complement of questionnaires, with focus groups or interviews that give a more profound context, with information on various experiences, worries and expectations of students. This approach can be complementary a highlight different perspectives, such as the reason why students view risk or the ways in which enjoyment does not convert into favorable opinions in educational settings.

Lastly considering the speed at which technology is developing, future research should investigate how students' views are impacted by new aspects of AI, such as multimodal interactions, more natural conversational skills and integration with learning management systems. To keep research in line with practice, it will be crucial to comprehend how developments in AI design after concepts like usefulness, value and risk.

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