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Master

Data Analytics for Business

Master's Final Work

Dissertation

Adoption of Generative Artificial Intelligence in Higher Education in Cabo Verde: An Analysis Based on an Extended UTAUT Model

Riana Monteiro

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Riana Monteiro

Supervision:

Prof. Carlos Manuel Jorge da Costa

January - 2026

“I can do all things through

Christ who strengthens me.”

— Philippians 4:13

GLOSSARY

AI - Artificial Intelligence

AVE - Average Variance Extracted

BI - Behavioral Intention

COPE - Committee on Publication Ethics

CR - Composite Reliability

DL - Deep Learning

EA - Ethical Attitude

EE - Effort Expectancy

FC - Facilitating Conditions

GenAI - Generative Artificial Intelligence

HM - Hedonic Motivation

ML - Machine Learning

OECD - Organization for Economic Co-operation and Development

PE - Performance Expectancy

PLS - Partial Least Squares

SEM - Structural Equation Modelling

SI - Social Influence

TAM - Technology Acceptance Model

TEQSA - Tertiary Education Quality and Standards Agency

TR - Trust

UB - Usage Behavior

UNESCO - United Nations Educational, Scientific and Cultural Organization

UTAUT - Unified Theory of Acceptance and Use of Technology

VADER - Valence Aware Dictionary and sEntiment Reasoner

ABSTRACT

Generative artificial intelligence (GenAI) is rapidly reshaping higher education, yet adoption depends not only on usefulness and ease of use but also on trust, ethics, and users' evaluative perceptions of its role. This dissertation examines GenAI adoption in higher education in Cabo Verde using an extended UTAUT/UTAUT2 model (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Hedonic Motivation) enriched with Trust and Ethical Attitude. Survey data from students, lecturers, and staff ($N = 210$) were analysed with PLS-SEM. In addition, responses to an optional open-ended question ($N = 69$) were examined through VADER-based sentiment analysis, a lexicon- and rule-based method applied to translated English text, to provide a descriptive indication of the polarity expressed toward GenAI.

The structural model accounts for a substantial proportion of variance in Behavioral Intention ($R^2 = 0.645$) and a moderate proportion of variance in Usage Behavior ($R^2 = 0.320$). In the model, Performance Expectancy is the strongest positive predictor of Behavioral Intention ($\beta = 0.426$, $p < 0.001$), followed by Hedonic Motivation ($\beta = 0.269$, $p < 0.001$) and Ethical Attitude ($\beta = 0.267$, $p = 0.001$). Social Influence is not statistically significant ($p = 0.126$). Effort Expectancy presents a statistically significant negative direct coefficient for Behavioral Intention ($\beta = -0.127$, $p = 0.025$), which is contrary to the hypothesised positive direction and therefore does not support H2. However, its indirect association with Behavioral Intention through Performance Expectancy is positive and statistically significant. Trust is positioned as an antecedent variable, showing strong positive associations with Ethical Attitude ($\beta = 0.620$, $p < 0.001$) and Social Influence ($\beta = 0.422$, $p < 0.001$).

The VADER-based sentiment analysis classified most responses as positive (72.5%), with smaller proportions classified as neutral/unclear (15.9%) and negative (11.6%). These results should be interpreted as exploratory descriptive evidence of textual polarity rather than as a full qualitative assessment of attitudes. Overall, the findings support extending UTAUT with trust- and ethics-related constructs and highlight practical priorities for governance, training, and responsible integration of GenAI in higher education in Cabo Verde.

KEYWORDS: GenAI; Higher Education; UTAUT; Trust; Ethical Attitude; Cabo Verde.

Resumo

Esta dissertação analisa a adoção da inteligência artificial generativa (GenAI) no ensino superior em Cabo Verde, utilizando um modelo alargado UTAUT/UTAUT2 que integra Expectativa de Desempenho, Expectativa de Esforço, Influência Social, Condições Facilitadoras e Motivação Hedónica, complementadas por Confiança e Atitude Ética. Os dados foram recolhidos junto de estudantes, docentes e funcionários (N = 210) e analisados com PLS-SEM. Adicionalmente, respostas a uma pergunta aberta opcional (N = 69) foram examinadas por análise de sentimento baseada no VADER, aplicada a texto traduzido para inglês, com finalidade exploratória e descritiva.

Os resultados mostram que o modelo explica uma proporção substancial da variância da Intenção Comportamental ($R^2 = 0,645$) e uma proporção moderada do Comportamento de Uso ($R^2 = 0,320$). A Intenção Comportamental é explicada sobretudo pela Expectativa de Desempenho ($\beta = 0,426$, $p < 0,001$), Motivação Hedónica ($\beta = 0,269$, $p < 0,001$) e Atitude Ética ($\beta = 0,267$, $p = 0,001$), enquanto a Influência Social não é significativa ($p = 0,126$). A Expectativa de Esforço apresenta um coeficiente direto negativo e significativo sobre a intenção ($\beta = -0,127$, $p = 0,025$), não suportando H2, embora a sua associação indireta via Expectativa de Desempenho seja positiva. A Confiança surge como antecedente relevante da Atitude Ética ($\beta = 0,620$, $p < 0,001$) e da Influência Social ($\beta = 0,422$, $p < 0,001$).

A análise VADER classificou 72,5% das respostas abertas como positivas, 15,9% como neutras/pouco claras e 11,6% como negativas. Estes resultados indicam polaridade textual predominantemente favorável, mas devem ser interpretados apenas como evidência exploratória, não como análise qualitativa completa. Em conjunto, os resultados sugerem que a adoção da GenAI é impulsionada pela utilidade percebida, pelo envolvimento e pela legitimidade ética, exigindo governação, formação e orientação institucional para um uso responsável no ensino superior em Cabo Verde.

Palavras-chave: GenAI; Ensino Superior; UTAUT; Confiança; Atitude Ética; Cabo Verde.

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First, I thank God for the gift of life, for all the blessings I have received, and for every person who has been part of my journey - without them, none of this would have been possible.

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1. Introduction

Since the pandemic, digital transformation has accelerated across higher education (OECD, 2021). Universities now rely more heavily on technology to support learning, research, and academic management. In this context, artificial intelligence (AI) has gained significant momentum, and generative artificial intelligence (GenAI) systems, capable of producing text, images, code, and other content in real time, have opened a new scale of possibilities (Dwivedi et al., 2023; Ray, 2023). This shift is reshaping study routines, academic writing practices, lesson preparation, and the design of learning activities (Sullivan et al., 2023).

Despite the potential benefits of GenAI, its rapid diffusion has outpaced the capacity of institutions to develop coherent policies, training, and governance mechanisms (UNESCO, 2023). This gap is especially relevant in higher education systems, where credibility in assessment and the development of critical thinking are central to educational value (TEQSA, 2024). In practice, the same tools that support learning and productivity can also create risks. Common concerns include academic integrity, authorship, dependency, misinformation, privacy, and fairness (COPE, 2024).

These opportunities and risks are driving a renewed need to understand not only whether GenAI is used, but also why it is accepted, resisted, or used with caution by diverse groups within the university environment (Granić, 2022; UNESCO, 2023). More broadly, research on the adoption of educational technologies indicates that a single factor rarely explains acceptance; rather, it reflects a combination of intrinsic and extrinsic variables (Granić, 2022).

As far as theory is concerned, research on technology adoption in education has traditionally been based on models that explain why individuals accept or reject innovations. Systematic evidence indicates that the Technology Acceptance Model (TAM) and related approaches have dominated research on educational technology adoption, also pointing to recurrent determinants such as enabling conditions, social norms, and pleasure-related factors (Granić, 2022).

Among the integrative frameworks, the Unified Theory of Technology Acceptance and Use (UTAUT) has been widely used to explain behavioral Intention and use behavior in multiple technological contexts, combining determinants that appear repeatedly in investigations on educational technology adoption in the most diverse regions (Dwivedi et al., 2019).

Despite the rapid growth of research on AI adoption, the evidence base remains uneven across regions. Much of the empirical work focuses on Europe, Asia, and North America, while African higher education perspectives remain underrepresented. This is important because the drivers of adoption are partly shaped by cultural norms, institutional policies, resource availability, and the maturity of digital ecosystems. Consequently, conclusions drawn in other contexts cannot be transferred mechanically to others. This motivates the need for local validation.

UNESCO's assessment work on AI capacity in Africa highlights persistent gaps in infrastructure, skills, and governance that can directly affect whether AI tools are adopted responsibly and at scale (UNESCO, 2021). This is the backdrop against which the case of Cabo Verde stands. Higher education in Cabo Verde has its own institutional dynamics, resources, and support structures. Because driver adoption depends on context, findings from other regions should not be transferred mechanically. For this reason, this dissertation examines the factors that enable—or inhibit—the adoption and effective Use of GenAI in higher education in Cabo Verde.

This study adopts the UTAUT/UTAUT2 perspective. It proposes a broad model that integrates Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC), adding Hedonic Motivation (HM) and strengthening the model with Trust (TR) and Ethical Attitude (EA) to capture particularly relevant dimensions in the adoption of GenAI in Higher education in Cabo Verde. This configuration reflects that GenAI adoption is shaped not only by utility but also by perceptions of risk, legitimacy, and evaluative judgment (Dwivedi et al., 2019; Joshi, 2025).

Based on this theoretical framework, the dissertation is guided by the following research questions:

- **RQ1:** What are the main factors that influence the behavioral Intention (BI) and actual usage behavior (UB) of GenAI in higher education in Cabo Verde?
- **RQ2:** Do Trust and Ethical Attitude significantly improve the explanatory power compared to the UTAUT base model?

- **RQ3:** What sentiment is revealed in the academic context toward GenAI?

This study contributes in three main ways. First, it provides empirical evidence on the adoption of GenAI in higher education in Cabo Verde — a context underrepresented in the existing literature, which remains concentrated in other regions and in larger systems. Secondly, it contributes theoretically by assessing a context-adapted extended UTAUT model that integrates Trust and ethical Attitude as mechanisms particularly relevant to GenAI in academic contexts. Third, it offers practical implications for universities and decision-makers by identifying which factors most support (or hinder) the responsible Use of GenAI, informing strategies for training, governance, infrastructure investment, and institutional guidance.

Methodologically, the study adopts a primarily quantitative approach, complemented by qualitative input, using survey data collected among higher education institutions in Cabo Verde and analyzed through PLS-SEM (SmartPLS). This approach is appropriate given the predictive orientation of the model and the need to estimate simultaneous relationships between multiple latent constructs.

This dissertation is organized as follows. Chapter 2 (Literature Review) introduces fundamental concepts of AI and GenAI and synthesizes how GenAI is being applied in higher education, including benefits and challenges. Chapter 3 (Theoretical Framework and Hypothesis Development) presents the extended UTAUT-based model and develops the hypothesised relationships. Chapter 4 (Methodology) details the research design, sampling approach, instrument development, data collection procedures, and data analysis strategy using SmartPLS. Chapter 5 (Results) reports the conclusions of the measurement and the structural model. Chapter 6 (Discussion) synthesizes the main findings, interprets the key relationships in light of theory and prior evidence, compares the results with related studies, and derives implications for higher education stakeholders in Cabo Verde. Finally, Chapter 7 (Conclusion) summarizes the main contributions, limitations, and orientations for future research.

2. Literature Review

2.1 AI and GenAI

Artificial Intelligence (AI) is usually described as a field of computing focused on building systems that can perform tasks linked to human cognition, such as learning, reasoning, and decision-making (Russell & Norvig, 2021). Early AI relied heavily on rule-based logic. That approach worked in controlled contexts, but it struggled with complex real-world problems.

A major shift happened with Machine Learning (ML). In ML, models learn patterns from data instead of depending only on pre-defined rules (Jordan & Mitchell, 2015). This approach became more viable as data availability increased, and computing power expanded. Within ML, Deep Learning (DL) introduced multi-layer neural networks that significantly improved performance in tasks like language processing and image recognition (LeCun et al., 2015). These developments created the foundations for modern large-scale AI systems.

Generative Artificial Intelligence (GenAI) represents a further step. Unlike analytical AI, which focuses on prediction, classification, or optimization, GenAI produces new outputs such as text, images, audio, or code (Jovanović & Campbell, 2022). This has been strongly enabled by transformer-based architecture, which made it possible to scale language modelling and support interactive, prompt-based Use (Vaswani et al., 2017, Costa, 2025). Because GenAI responds conversationally and iteratively, it is perceived less as a "tool in the background" and more as a visible partner in knowledge work.

In education, the distinction between analytical AI and GenAI is not only technical. It affects how students and staff use technology, and it also changes the risk profile. This is one reason international guidance has placed strong emphasis on governance and responsible use, especially when GenAI becomes widely accessible to learners (UNESCO, 2023). At the user level, recent work also links adoption to AI literacy, meaning the ability to understand, evaluate, and use AI outputs critically and ethically (Qi et al., 2025). Without these competencies, users may adopt quickly but apply the tools in ways that reduce learning quality or increase integrity risks (Qi et al., 2025).

Table 1 summarizes the most relevant differences for higher education research.

TABLE I - CONCEPTUAL AND FUNCTIONAL DISTINCTIONS BETWEEN TRADITIONAL AI AND GENAI

Dimension	Traditional AI (Analytical)	Generative AI (GenAI)
Main function	Analyze, classify, predict, optimize	Generate updated content (text, images, code)
Interaction	Task-oriented, often indirect	Prompt-based, conversational, iterative
Typical educational use	Learning analytics, adaptive systems	Drafting, ideation, tutoring-style support
Key risks	Bias, opacity, automated unfairness	Hallucinations, integrity issues, and overreliance
Evaluation focus	Accuracy and error reduction	Usefulness, factuality, integrity, and transparency

Note. Based on the educational framing of GenAI and responsible-use guidelines (UNESCO, 2023) and adoption-focused literature emphasizing distinct risks and evaluation criteria for generative systems (Qi et al., 2025; Zhao et al., 2024).

2.2 GenAI in Higher Education

GenAI has moved into daily academic practice faster than most educational technologies. Many students already use these tools for brainstorming, organizing ideas, drafting text, summarizing materials, or supporting coding tasks (Zhao et al., 2024). Faculty and staff also explore GenAI to support teaching preparation, streamline academic routines, and reduce time spent on repetitive administrative work (Baig & Yadegaridehkordi, 2025). In research contexts, GenAI can assist with early-stage exploration of themes or quick scanning of large volumes of text, although results still require verification and scholarly judgement (Aparício et al., 2024; Zhao et al., 2024).

From a pedagogical point of view, GenAI is often framed as a tool that can support learning through interaction. Its conversational format can provide immediate guidance, examples, or alternative explanations. This can be valuable where students have limited access to one-to-one support (UNESCO, 2023). In principle, this type of support may help learners progress through difficult steps more efficiently and spend more time on deeper reasoning. However, this outcome depends on how the tool is used and how students are guided. AI literacy becomes crucial here because students need the ability to question outputs rather than accept them passively (Qi et al., 2025).

The potential benefits are often linked to productivity and perceived performance gains. In adoption studies, performance-related perceptions are commonly associated with stronger intentions to use GenAI (Zhao et al., 2024). This is consistent with evidence showing that users tend to adopt when they believe the tool improves efficiency or results (Masrek et al., 2025). Enjoyment and curiosity can also matter, especially during early experimentation, because interactive GenAI tools feel engaging and easy to explore (Masrek et al., 2025).

At the same time, GenAI adoption in higher education comes with risks that are unusually sensitive in academic environments. Academic integrity is one of the most visible concerns. When GenAI produces well-written content, it can blur boundaries between legitimate support and inappropriate substitution, especially if guidance on attribution and acceptable Use is unclear (UNESCO, 2023). Overreliance is another risk. If students delegate core reasoning and synthesis tasks to GenAI, learning can become more superficial, with weaker development of critical thinking and argumentation (Zhao et al., 2024). Reliability is also a persistent limitation. GenAI may generate persuasive but incorrect content, which becomes a significant issue when users do not verify outputs or do not have enough domain knowledge to detect errors (Alotaibi, 2025).

Ethical and institutional challenges further complicate adoption. GenAI can reproduce bias present in training data, which raises concerns about fairness and social harm (UNESCO, 2021). Privacy is another major issue, especially when students or staff share sensitive information with third-party systems (UNESCO, 2023). In practice, these concerns strongly connect to Trust. Studies that integrate Trust into UTAUT-style models show that Trust can shape intention and sustained usage, particularly when perceived risk and uncertainty are high (Joshi, 2025). In higher education contexts, Trust also appears relevant to continuous usage among academic staff, together with satisfaction and institutional support conditions (Baig & Yadegaridehkordi, 2025). Related evidence from university-student studies suggests that Trust can also play a mediating role between adoption and academic outcomes (Alotaibi, 2025).

Overall, the literature points to a clear conclusion. GenAI adoption cannot be explained only by usefulness or ease of Use. It is shaped by support conditions, competence and literacy, Trust, and ethical judgement, which is why technology acceptance frameworks remain useful for studying GenAI in higher education (Masrek et al., 2025; Qi et al., 2025; Zhao et al., 2024).

This leads directly to the next chapter, where the dissertation specifies an extended UTAUT-based model to examine which factors are most relevant in the higher education in Cabo Verde context.

3. Theoretical Framework and Hypothesis Development

3.1 Research Context and Model Selection

Research on technology adoption in education has consistently relied on structured acceptance models to explain why students and educators integrate or reject new digital tools. A systematic review by Granić (2022), analyzing educational technology adoption between 2003 and 2021, demonstrates that the literature has been dominated by the Technology Acceptance Model (TAM) and its extensions. However, the Unified Theory of Acceptance and Use of Technology (UTAUT) has emerged as a more robust and integrative framework, providing a comprehensive explanation of behavioral Intention and actual usage across diverse institutional settings (Venkatesh et al., 2003).

Despite its merits, the consolidation of UTAUT has raised theoretical challenges regarding contextual sensitivity. Venkatesh et al. (2016) emphasized the need for stronger cross-context theorizing, particularly in the context of disruptive technologies. This is especially relevant for Generative Artificial Intelligence (GenAI), where usage decisions depend not only on utilitarian benefits but also on perceptions of risk, legitimacy, and academic appropriateness. Consequently, this study adopts a revised UTAUT approach, as suggested by Dwivedi et al. (2019), incorporating dimensions that capture the psychological and value-based evaluation of behaviors, specifically Trust and Ethical Attitude.

3.2 Construct Definitions

The present study adopts UTAUT as its core framework and incorporates elements from **UTAUT2** (Hedonic Motivation), complemented by dimensions critical to the "generative turn" in higher education. The following table defines these constructs within the specific context of GenAI.

TABLE II - DEFINITIONS OF CONSTRUCTS IN THE GENAI CONTEXT

Construct	Adapted Description	Primary Sources
Performance Expectancy (PE)	The degree to which users believe GenAI improves academic performance, teaching efficiency, and learning outcomes.	Venkatesh et al. (2003)
Effort Expectancy (EE)	The degree of perceived ease in using generative AI tools for educational activities.	Venkatesh et al. (2003)
Social Influence (SI)	To the degree to which users perceive that important others (peers, leaders) expect them to Use GenAI.	Venkatesh et al. (2003)
Facilitating Conditions (FC)	The degree to which individuals believe there are resources and institutional support for using GenAI.	Venkatesh et al. (2003)
Trust (TR)	The degree of confidence in the reliability, ethics, and security of generative AI tools.	Gefen et al. (2003); McKnight et al. (2011)
Hedonic Motivation (HM)	The enjoyment or pleasure derived from interacting with and exploring conversational AI.	Venkatesh et al. (2012) Fu et al. (2024)
Ethical Attitude (EA)	Judgements about the responsible, fair, and transparent Use of GenAI in academic tasks.	Verma & Garg (2023)

Behavioral Intention (BI)	The degree to which an individual intends to adopt and continue using GenAI.	Venkatesh et al. (2003)
Usage Behavior (UB)	The actual frequency and depth of GenAI tool usage in academic practice.	Venkatesh et al. (2003)

3.3 Proposed conceptual model

The structural model adopted in this dissertation posits that Behavioral Intention (BI) is directly influenced by five determinants: PE, EE, SI, HM, and EA. BI then determines Usage Behavior (UB). In addition, the model includes three antecedent relationships that support the formation of these perceptions: FC influences EE, EE influences PE, and TR influences SI and EA.

This configuration captures (i) classic acceptance factors (perceived benefit, ease of Use, and social norms), (ii) motivational factors (enjoyment/engagement), and (iii) factors that are particularly critical for GenAI (Trust and ethics), while keeping the model sufficiently parsimonious for a robust analysis in the higher education in Cabo Verde context.

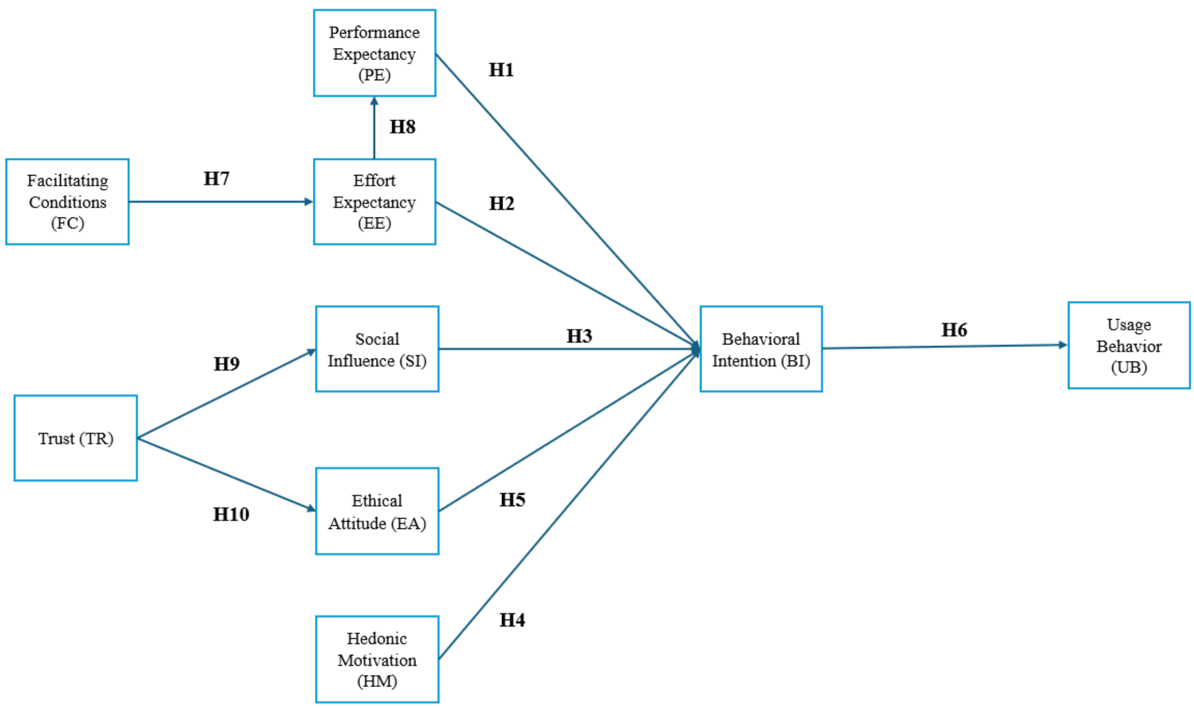

FIGURE 1 - Proposed conceptual model

3.4 Hypothesis Development

The structural model posits that Behavioral Intention (BI) is the central driver of adoption, influenced by utilitarian, social, hedonic, and ethical determinants.

H1: Performance Expectancy (PE) positively influences Behavioral Intention (BI).

UTAUT proposes that PE is a consistent predictor of intention because individuals adopt technologies when they expect clear productivity gains. In the GenAI context, perceived usefulness is especially relevant because these tools can accelerate task completion, support academic writing, assist ideation, and extend access to advanced digital capabilities (Venkatesh et al., 2003; Costa, 2025; Costa et al., 2024; Zhao et al., 2024).

H2: Effort Expectancy (EE) positively influences Behavioral Intention (BI).

Ease of Use is crucial for innovative technologies. The more intuitive the GenAI interaction, the more likely users are to integrate it into their practices (Venkatesh et al., 2003)

H3: Social Influence (SI) positively influences Behavioral Intention (BI).

In universities, social norms and peer practices significantly shape technological behavior. Peer validation and institutional expectations increase the Intention to use GenAI (Venkatesh et al., 2003)

H4: Hedonic Motivation (HM) positively influences Behavioral Intention (BI).

The enjoyment and engagement associated with the "conversational" user experience in GenAI strengthen the user's Intention to continue exploring the tool (Venkatesh et al., 2012; Fu et al., 2024).

H5: Ethical Attitude (EA) positively influences Behavioral Intention (BI).

EA is critical because GenAI use raises dilemmas regarding authorship, integrity, fairness, and transparency. When users believe that GenAI can be used responsibly and ethically, intention is expected to increase; however, negative ethical perceptions may inhibit adoption even when usefulness is high (Verma & Garg, 2023; Veiga & Costa, 2024; Costa et al., 2024).

H6: Behavioral Intention (BI) positively influences Usage Behavior (UB).

In accordance with UTAUT’s core logic, individuals with stronger intentions are significantly more likely to translate that predisposition into actual behavior (Venkatesh et al., 2003).

H7: Facilitating Conditions (FC) positively influence Effort Expectancy (EE).

Access to infrastructure, support, and institutional resources reduces practical friction, strengthening the perception that GenAI is easy to Use (Venkatesh et al., 2003).

H8: Effort Expectancy (EE) positively influences Performance Expectancy (PE).

When technology is perceived as easy to Use, users more readily recognize its performance potential, as the lower "learning cost" makes benefits more attainable (Venkatesh et al., 2003; Dwivedi et al., 2019).

H9: Trust (TR) positively influences Social Influence (SI).

In the GenAI context, trust serves as a foundation for legitimizing use. When users trust the safety, reliability, and institutional appropriateness of a technology, they may become more receptive to positive social signals and peer recommendations. This is consistent with AI democratization arguments that adoption depends not only on access but also on responsible and meaningful use (Costa et al., 2024; Masrek et al., 2025; Joshi, 2025).

H10: Trust (TR) positively influences Ethical Attitude (EA).

Trust reduces perceived risk and supports a positive view of responsible use. Greater trust increases the predisposition to consider GenAI ethically acceptable for academic tasks, consistent with evidence that ethical attitudes are central to AI adoption when privacy, security, and responsible data use are salient (Gefen et al., 2003; McKnight et al., 2011; Veiga & Costa, 2024).

4. METHODOLOGY

4.1 Research design

This study adopts a quantitative, cross-sectional research design based on a survey methodology. The objective is to empirically test the relationships between latent constructs derived from the UTAUT model and its extensions in the context of GenAI adoption in higher education.

The research model was analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM), which is appropriate for predictive research, theory extension, and models with multiple latent constructs. In addition to the quantitative component, the study includes a complementary textual component based on an open-ended question. This component was analysed through VADER-based sentiment analysis to provide descriptive evidence of polarity in respondents' comments, rather than to replace a full qualitative content or thematic analysis.

4.2 Population, sampling, and data collection

The target population comprises higher education stakeholders in Cabo Verde, including students, lecturers, and other staff, as these groups are directly involved in academic and organisational activities where GenAI tools may be applied.

Data were collected using an online questionnaire (Google Forms). A non-probability convenience sampling strategy was used, and the questionnaire link was disseminated through institutional and informal academic channels to reach participants across different higher education contexts. Participation was voluntary, and responses were collected anonymously and treated confidentially for academic purposes.

Data collection occurred between 9 November and 18 December 2025. After initial screening (missing values, inconsistent responses, and incomplete submissions), the final dataset included 210 valid responses (N = 210) suitable for analysis.

TABLE III - SAMPLE CHARACTERISTICS

Characteristic	Summary
Gender	Female: 150 (71.4%); Male: 60 (28.6%)
Age	Mean = 24.95; SD = 7.91; Min = 17; Max = 61
Key role	Student: 189 (90.0%); Lecturer: 17 (8.1%); Other staff: 4 (1.9%)
GenAI use frequency	Several times/day: 65 (31.0%); Several times/week: 64 (30.5%)

In usage terms, GenAI is already embedded in the academic routines of a substantial share of respondents: 61.5% report using GenAI several times per week or more. This pattern supports the relevance of modelling both intention and actual Use, since GenAI adoption is not merely occasional experimentation in this sample.

4.3 Measurement instrument and construct operationalization

The questionnaire was composed of two main sections. The first section collected demographic and contextual information to characterise the sample and GenAI usage patterns. The second section included measurement items for the latent constructs of the research model.

All constructs were measured using validated multi-item reflective scales, adapted from prior literature to the GenAI context. Responses were recorded on a seven-point Likert scale, ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). The construct Usage Behavior was operationalised as a single-item measure capturing the frequency of GenAI use, consistent with previous UTAUT-based studies.

To mitigate potential common method bias, respondents were assured of anonymity, and no right or wrong answers were implied. In addition, collinearity diagnostics were later examined during structural model assessment.

TABLE IV - SURVEY CONSTRUCTS (MEASUREMENT SUMMARY)

Construct	Role in the model	Scale type
PE, EE, SI, FC, HM, TR, EA, BI	Latent predictors/mediators of intention and usage	Reflective multi-item (Likert 1–7)
UB	Outcome (usage behavior)	Single-item frequency measure

4.4 Data analysis procedure

Data analysis was carried out using SmartPLS and the PLS-SEM approach, which allows the simultaneous evaluation of the measurement and structural components of the model. Following standard recommendations in PLS-SEM research, the analysis was conducted in two sequential stages.

In Step 1 (measurement model assessment), the quality of the reflective measurement model was examined by assessing indicator reliability (outer loadings), internal consistency reliability (Cronbach's alpha and Composite Reliability), convergent validity (Average Variance Extracted - AVE), and discriminant validity. Discriminant validity was evaluated using both the HTMT criterion and the Fornell–Larcker criterion, providing complementary evidence that the constructs are empirically distinct.

In Step 2 (structural model assessment), the structural model was evaluated by analysing collinearity diagnostics (VIF), explanatory power (R^2 values of endogenous constructs), and the significance of the hypothesised relationships. Path significance was tested using a bootstrapping procedure with 5,000 subsamples, which enabled the estimation of standard errors, t-values, and p-values for the structural coefficients.

4.5 Complementary qualitative procedure: sentiment analysis

To complement the quantitative findings, the questionnaire included an optional open-ended question regarding the future role of Generative Artificial Intelligence (GenAI) in higher education in Cabo Verde: *"What is your view on the future role of GenAI in higher education in Cabo Verde?"* A total of 69 usable textual responses were collected.

These comments were analysed using an exploratory sentiment analysis procedure designed to complement the quantitative findings and address RQ3. Because VADER is primarily an English-language lexicon- and rule-based tool, and because responses were written predominantly in Portuguese, the comments were translated into English before automated scoring. The translation step improves compatibility with the VADER lexicon, but it also introduces a methodological limitation because some sentiment-bearing expressions may change in intensity or nuance during translation. For this reason, the sentiment results are interpreted cautiously and descriptively.

Sentiment scoring was performed in Python using VADER (Valence Aware Dictionary and sEntiment Reasoner), developed by Hutto and Gilbert (2014). VADER is a lexicon- and rule-based sentiment analysis method originally designed for short and informal texts. It combines a sentiment lexicon with rules for features such as negation, intensifiers, punctuation, capitalization, and contrastive conjunctions. For each response, VADER returns positive, neutral, and negative proportions and a compound score ranging from -1 to +1, where higher values indicate more positive textual polarity.

The procedure had two stages. First, each translated response was automatically scored using VADER's compound score and classified into one of three polarity categories. Second, because the responses were translated and because VADER can misclassify short, ambiguous, or domain-specific statements, a manual plausibility check was conducted. This check was not intended to recode the data systematically; rather, it was used to assess whether the automated classifications were broadly coherent with the semantic content of the responses.

Classification followed the standard VADER thresholds: responses were classified as positive when the compound score was greater than or equal to 0.05, negative when it was less than or equal to -0.05, and neutral/unclear when it fell between -0.05 and 0.05. The resulting categories were used only as descriptive indicators of expressed polarity in the open-ended comments. They should not be interpreted as statistically generalisable measures of attitudes or as substitutes for thematic coding.

TABLE V - SENTIMENT CLASSIFICATION CRITERIA

Category	Compound score rule	Interpretation
Positive	compound ≥ 0.05	Overall positive evaluation
Negative	compound ≤ -0.05	Overall negative evaluation
Neutral/Unclear	$-0.05 <$ compound < 0.05	No dominant polarity / unclear stance

5. RESULTS

5.1 Measurement model results

The measurement model was evaluated for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Table VI summarises outer loadings together with construct-level reliability (composite reliability and Cronbach's alpha), AVE, and indicates if each construct has discriminant validity.

TABLE VI - MEASUREMENT MODEL RESULTS

Construct	Item	Loading	CR	α	AVE	Discriminant validity?
BI	BI1	0.887	0.938	0.900	0.833	Yes
	BI2	0.910				
	BI3	0.941				
EA	EA1	0.853	0.920	0.869	0.793	Yes
	EA2	0.899				
	EA3	0.918				
EE	EE1	0.900	0.922	0.874	0.799	Yes
	EE2	0.900				
	EE3	0.881				

FC	FC1	0.860	0.841	0.718	0.641	Yes
	FC2	0.866				
	FC3	0.659				
HM	HM1	0.868	0.924	0.876	0.801	Yes
	HM2	0.911				
	HM3	0.905				
PE	PE1	0.787	0.878	0.814	0.643	Yes
	PE2	0.861				
	PE3	0.836				
	PE4	0.716				
SI	SI1	0.887	0.938	0.901	0.835	Yes
	SI2	0.927				
	SI3	0.926				
Trust	TR1	0.827	0.895	0.823	0.740	Yes
	TR3	0.878				
	TR4	0.874				
Use	UB1	1.000	Single-item	—	—	Yes

Most indicators exceed the 0.70 guideline, supporting indicator reliability. One Facilitating Conditions indicator (FC3 = 0.659) is slightly below 0.70, but was retained to preserve construct content coverage; the FC construct still meets reliability and AVE requirements. Usage behaviour was modelled as a single-item construct (Use/UB1 = 1.000), consistent with the questionnaire design. Trust is represented by three indicators (TR1, TR3, TR4).

Discriminant validity was examined using HTMT and additionally checked using the Fornell–Larcker criterion. HTMT values remain below commonly used thresholds (0.85/0.90), and the Fornell–Larcker condition is satisfied across constructs, supporting discriminant validity.

TABLE VII - FORNELL–LARCKER CRITERION

	BI	EA	EE	FC	HM	PE	SI	Trust	Use
BI	0.91	0.65	0.42	0.42	0.66	0.70	0.49	0.57	0.57
EA	0.65	0.89	0.42	0.45	0.58	0.55	0.42	0.62	0.31
EE	0.42	0.42	0.89	0.64	0.46	0.62	0.44	0.41	0.36
FC	0.42	0.45	0.64	0.80	0.46	0.47	0.45	0.46	0.33
HM	0.66	0.58	0.46	0.46	0.90	0.58	0.46	0.52	0.39
PE	0.70	0.55	0.62	0.47	0.58	0.80	0.48	0.47	0.45
SI	0.49	0.42	0.44	0.45	0.46	0.48	0.91	0.42	0.34
Trust	0.57	0.62	0.41	0.46	0.52	0.47	0.42	0.86	0.27
Use	0.57	0.31	0.36	0.33	0.39	0.45	0.34	0.27	1.00

5.2 Structural model results

After establishing measurement quality, the structural model was evaluated in terms of collinearity, explanatory power (R^2), and hypothesis testing using bootstrapping (5,000 subsamples).

Collinearity was assessed using inner VIF values. All VIF values are low (maximum = 2.155), indicating no problematic multicollinearity among predictor constructs.

TABLE VIII - INNER VIF

Path	**VIF**
BI -> Use	1.000
EA -> BI	1.715

EE -> BI	1.714
EE -> PE	1.000
FC -> EE	1.000
HM -> BI	1.862
PE -> BI	2.155
SI -> BI	1.453
Trust -> EA	1.000
Trust -> SI	1.000

The model explains a substantial share of variance in Behavioral Intention (BI) and a moderate share in Usage Behavior (Use), consistent with UTAUT-style models where intention is typically more predictable than actual behaviour.

TABLE IX - EXPLAINED VARIANCE (R^2)

Endogenous construct	R^2	R^2 adjusted
BI	0.645	0.636
Use	0.320	0.317
EE	0.414	0.411
PE	0.382	0.379
EA	0.385	0.382
SI	0.178	0.174

Bootstrapping results were used to assess the statistical significance of the hypothesised structural relationships. The results indicate that Behavioral Intention is positively predicted by Performance Expectancy (PE), Hedonic Motivation (HM), and Ethical Attitude (EA), while Social Influence (SI) does not show a statistically significant association with Behavioral Intention in this model. Effort Expectancy (EE) has a statistically significant negative direct coefficient for Behavioral Intention; because the hypothesised relationship was positive, H2 is not supported. Trust is not modelled as a direct predictor of Behavioral Intention; instead, it is specified as an antecedent of Ethical Attitude and Social Influence. Behavioral Intention, in turn, is positively associated with Usage Behavior.

TABLE X - HYPOTHESIS TEST RESULTS (BOOTSTRAPPING)

Hypothesis	**Independent -> Dependent**	**Finding**	**p-value**	**Conclusion**
H1	PE influences BI	Positive and significant (β = 0.426)	<0.001	Supported
H2	EE influences BI	Negative and significant (β = -0.127)	0.025	Not supported; opposite sign
H3	SI influences BI	Not significant (β = 0.102)	0.126	Not supported
H4	HM influences BI	Positive and significant (β = 0.269)	<0.001	Supported
H5	EA influences BI	Positive and significant (β = 0.267)	0.001	Supported
H6	BI influences Use	Positive and significant (β = 0.566)	<0.001	Supported
H7	FC influences EE	Positive and significant (β = 0.643)	<0.001	Supported
H8	EE influences PE	Positive and significant (β = 0.618)	<0.001	Supported
H9	Trust influences SI	Positive and significant (β = 0.422)	<0.001	Supported
H10	Trust influences EA	Positive and significant (β = 0.620)	<0.001	Supported

The results for Effort Expectancy (EE) require careful interpretation. The direct coefficient from EE to Behavioral Intention is negative and statistically significant, whereas the hypothesis expected a positive relationship. Therefore, H2 is not supported. At the same time, EE has a strong positive coefficient for Performance Expectancy, and the indirect effect of EE on Behavioral Intention through Performance Expectancy is positive and statistically significant. Scientifically, this pattern should be interpreted as evidence of an indirect mechanism, not as support for a positive direct effect. A possible explanation is a suppression or competitive mediation pattern, in which the variance in EE that is independent of Performance Expectancy is negatively associated with intention after other predictors are controlled. Substantively, ease of use appears to matter mainly because it increases perceived usefulness.

TABLE XI - MEDIATION ANALYSIS FOR EE ON BI

Effect	**Path**	**β**	**p-value**
Direct effect	EE influences BI	-0.127	0.025
Indirect effect	EE influences BI through PE	0.263	<0.001
Total effect	EE on BI (total)	0.137	0.027

5.3 Complementary analysis: sentiment analysis of the open-ended question

To complement the quantitative results, an exploratory sentiment analysis was conducted on the open-ended item: “What is your view on the future role of GenAI in higher education in Cabo Verde?” (N = 69). Responses were originally written predominantly in Portuguese and were translated into English before automated analysis because VADER is based mainly on an English sentiment lexicon. Sentiment was computed in Python using VADER, which returns positive, neutral, and negative proportions and a normalized compound score ranging from -1 to +1. The standard VADER thresholds were applied: positive when compound ≥ 0.05, negative when compound ≤ -0.05, and neutral/unclear when $-0.05 <$ compound < 0.05. Therefore, the results represent automated polarity classification of translated textual comments, not a full qualitative interpretation of participants’ views.

TABLE XII - SENTIMENT DISTRIBUTION OF OPEN-ENDED RESPONSES

Category	**n**	**%**
Positive	50	72.5
Neutral/Unclear	11	15.9
Negative	8	11.6

The distribution indicates that most translated comments express positive polarity toward GenAI's future role in higher education. However, this result must be interpreted with caution. VADER identifies lexical polarity rather than underlying meaning, and its performance may be affected by translation from Portuguese into English, short answers, irony, ambiguity, or domain-specific terminology. A manual plausibility check of the neutral/unclear and negative responses showed that the automated categories were broadly reasonable, but also confirmed some limitations: very short endorsements may be classified as neutral because they contain limited lexical signal, and some comments may be classified as negative because they include risk-related terms such as "prejudice," "dependence," or "plagiarism," even when the overall stance is conditional rather than entirely negative. Accordingly, the sentiment analysis is used as complementary descriptive evidence of polarity, while substantive interpretation still depends on the broader quantitative model and the qualitative meaning of the comments.

6. Discussion

6.1 Overview of the main findings

The proposed extended UTAUT model accounts for a substantial proportion of variance in Behavioral Intention (BI) ($R^2 = 0.645$) and a moderate proportion of variance in Usage Behavior (UB) ($R^2 = 0.320$). These results should be interpreted as explanatory and predictive evidence within a cross-sectional PLS-SEM design, not as proof of causal effects. The positive and statistically significant coefficient between BI and UB ($\beta = 0.566$; $p < 0.001$) supports the expected association between stronger intention and higher self-reported use.

Regarding the determinants of BI, the results show that GenAI adoption in higher education in Cabo Verde is mainly associated with three positive predictors: instrumental value, represented by Performance Expectancy (PE) ($\beta = 0.426$; $p < 0.001$); engagement, represented by Hedonic Motivation (HM) ($\beta = 0.269$; $p < 0.001$); and ethical legitimacy, represented by Ethical Attitude (EA) ($\beta = 0.267$; $p = 0.001$). Social Influence (SI) is not statistically significant ($p = 0.126$), meaning that the data do not provide sufficient evidence that perceived social pressure is independently associated with intention after the other predictors are included. Effort Expectancy (EE) requires a more nuanced interpretation: its direct coefficient on BI is negative and statistically significant, contrary to the hypothesised positive direction, while its indirect association with BI through PE is positive. Thus, ease of use should be understood as contributing to intention mainly by strengthening perceived usefulness, rather than as a positive direct predictor of intention in this model. The upstream relationships further clarify the model: Facilitating Conditions (FC) are positively associated with EE ($\beta = 0.643$; $p < 0.001$), EE is positively associated with PE ($\beta = 0.618$; $p < 0.001$), and Trust (TR) is positively associated with EA ($\beta = 0.620$; $p < 0.001$) and SI ($\beta = 0.422$; $p < 0.001$).

The open-ended component provides complementary descriptive evidence. The VADER-based analysis classified most translated comments as positive (72.5%), suggesting that many respondents used language expressing optimism about GenAI's future role in higher education in Cabo Verde. However, because VADER is a lexicon- and rule-based polarity tool, these percentages should not be interpreted as precise measures of attitudes or as results of a full qualitative analysis. Neutral/unclear responses (15.9%) and negative responses (11.6%) also indicate the presence of concerns related to dependence, reduced critical thinking, academic integrity, and responsible use. Overall, the sentiment results are consistent with the quantitative findings: adoption appears to be supported by perceived usefulness and engagement, but conditioned by ethics, trust, and responsible-use concerns.

6.2 Interpretation of key relationships considering theory and prior evidence

Performance Expectancy (PE) as the central driver of intention

The strongest determinant of BI is PE, indicating that GenAI adoption is primarily value-driven: respondents intend to use GenAI when they believe it improves productivity, speeds up tasks, or enhances academic outputs. This aligns with UTAUT's core proposition that performance benefits are the most stable and context-general predictor of intention. In the GenAI context, the centrality of PE is consistent with recent adoption framing that highlights performance gains (e.g., drafting, explaining, brainstorming) as the primary "entry point" for use in higher education.

Hedonic Motivation (HM): engagement matters for interactive GenAI

HM has a significant positive effect on BI, which is theoretically coherent with UTAUT2 and with the distinctive user experience of conversational GenAI. Unlike many institutional systems, GenAI tools encourage experimentation and iterative interaction; enjoyment and curiosity can therefore sustain continued intention beyond "pure usefulness." This finding supports the view that adoption of interactive AI in education is partly driven by engagement mechanisms (exploration, immediacy, perceived creativity), especially among student populations.

Ethical Attitude (EA): adoption is filtered by legitimacy and academic norms

EA is a significant predictor of BI, which highlights a GenAI-specific feature of adoption in education: students and lecturers evaluate not only whether GenAI is effective, but also whether its use is academically acceptable. This supports the theoretical rationale for extending UTAUT with ethics-related constructs when technologies intersect with authorship, assessment credibility, and integrity norms. The open-ended comments reinforce this mechanism: even supportive respondents frequently frame adoption as conditional on responsible use, rules, and avoidance of copy–paste behavior.

Social Influence (SI) is not significant: adoption is more individual than norm-driven

The non-significant relationship between SI and BI suggests that GenAI adoption in higher education in Cabo Verde is currently driven more by individual beliefs (value, engagement, legitimacy) than by stable social norms or institutional expectations. A plausible explanation is that GenAI use is still relatively informal and self-directed, while institutional guidance and shared norms remain emergent. In such settings, social cues may be weak or ambiguous, reducing the role of SI despite the technology's visibility.

Effort Expectancy (EE): a "suppressed" direct effect but meaningful indirect mechanism

EE has a negative and statistically significant direct coefficient for BI, while also showing a strong positive coefficient for PE. This means that the hypothesised positive direct effect of EE on BI is not supported. The positive total effect reported in the mediation analysis results from the indirect pathway through PE and should not be interpreted as evidence that ease of use directly increases intention. A scientifically cautious interpretation is that the model reveals a competitive or suppressor pattern: after perceived usefulness and other predictors are controlled, the residual component of ease of use is negatively associated with intention. Therefore, the substantive conclusion is that ease of use contributes to adoption primarily by making GenAI more useful or beneficial in users' perceptions.

Facilitating Conditions (FC) enable ease and reduce friction

The strong relationship between FC and EE indicates that institutional resources, access, and support mechanisms reduce practical friction, strengthening the perception that GenAI is easy to use. This is particularly relevant in settings where infrastructure, training, and governance vary across institutions. The finding supports the broader view in GenAI-in-education literature that readiness conditions, including training, access, support, and guidance, shape whether GenAI can be integrated responsibly rather than used ad hoc.

Trust (TR) operates upstream through ethical legitimacy

Trust shows strong positive associations with EA and SI. However, because SI is not statistically associated with BI while EA is, the findings are more consistent with an ethical-legitimacy pathway than with a social-pressure pathway. In this model, Trust does not directly explain intention; rather, it is associated with stronger ethical acceptance, and ethical acceptance is associated with intention. This interpretation is theoretically relevant for GenAI in higher education, where adoption decisions are shaped not only by perceived utility but also by concerns about responsibility, integrity, privacy, and legitimacy. The finding is consistent with prior evidence that ethical attitudes can be central to AI adoption when perceived risks and responsible use are salient (Veiga & Costa, 2024).

6.3 Comparison with related studies

Overall, the pattern of results is consistent with UTAUT-family research in the sense that PE remains the central determinant of Intention, and BI predicts usage. At the same time, the GenAI context produces meaningful deviations: ethical acceptance and Trust become more structurally important, and SI may weaken when institutional norms are unclear.

A direct comparison can be made with Correia (2025). Both studies support the importance of performance-related beliefs and confirm that ease of use may operate indirectly once usefulness or performance is included in the model. However, the pattern differs in relevant ways. First, the relationship between EE and BI is not significant in Correia (2025), whereas in the present study EE has a statistically significant negative direct coefficient and a positive indirect effect through PE. This means that H2 is not supported in the expected direction, even though EE still contributes positively to intention through perceived usefulness. Second, the role of Trust differs: Correia (2025) models Trust as directly associated with intention, whereas in this study Trust is positioned upstream, mainly through EA. This difference is theoretically plausible in higher education contexts where Trust is closely tied to integrity and legitimacy concerns rather than only to system reliability. Finally, SI is significant in Correia (2025) but not in this study. This may reflect contextual differences in the strength of institutional norms: in higher education in Cabo Verde, GenAI use may still be informal and self-directed, which can weaken the independent predictive role of social pressure.

The sentiment evidence should be read in the same cautious manner. The predominance of positive VADER classifications suggests favourable textual polarity, but the automated method does not capture the full complexity of respondents' reasoning. Several comments combine optimism with conditions, warnings, or ethical reservations. Therefore, the sentiment analysis does not prove uniformly positive attitudes; rather, it indicates that positive language is dominant while risk-related concerns remain visible in the open-ended responses. This pattern is consistent with international guidance on responsible GenAI use in education and with the dissertation's argument that adoption should be understood through both perceived benefits and perceived legitimacy.

TABLE XIII - SUMMARY OF ALIGNMENT BETWEEN THIS STUDY AND PRIOR EVIDENCE

Relationship / Mechanism	**This study**	**Consistency with prior UTAUT/GenAI evidence**
PE influences BI	Strong, positive, significant	Aligns with UTAUT's core proposition that performance benefits drive intention
HM influences BI	Positive, significant	Aligns with UTAUT2 logic that enjoyment supports intention in interactive technologies
EA → BI	Positive, significant	EA influences BI
SI → BI	Not significant	SI influences BI
EE influences BI through PE	Indirectly positive via PE	Consistent with the "ease supports usefulness/value" mechanism
TR influences BI through EA	Strong upstream ethics pathway	Highlights Trust as a legitimacy condition in higher education GenAI use

6.4 Implications for higher education in Cabo Verde

These findings translate into a coherent set of actionable priorities for universities and policymakers in Cabo Verde. First, institutions should prioritize the communication of concrete value cases, given that Performance Expectancy emerged as the strongest driver of behavioral intention. Highlighting specific academic use cases aligned with learning outcomes, such as concept explanation, brainstorming support, and structured feedback, can reinforce students' and educators' perception of GenAI's practical benefits.

At the same time, ethical governance must be strengthened. Clear guidelines on acceptable use, disclosure norms, and academic integrity rules are needed, alongside a redesign of assessment methods that reduces incentives for misuse while preserving core learning objectives. This recommendation responds directly to the ethical filter identified in both the quantitative and qualitative findings, underscoring that adoption cannot be encouraged without a parallel commitment to responsible use.

Equally important is investment in enabling conditions. Facilitating Conditions—including training, access to technology, and institutional support—play a critical role in reducing friction associated with adoption. Beyond their direct effect, these conditions also exert an indirect influence by enhancing perceived ease of use and performance expectancy, thereby reinforcing the broader adoption pathway.

Trust, too, must be cultivated through practice rather than assumed. Addressing concerns related to reliability and privacy requires deliberate efforts to teach verification habits, such as source checking and triangulation, together with data-aware usage practices. These measures not only build trust but also reinforce ethical acceptance among users.

Finally, concerns regarding overdependence on GenAI tools should be explicitly mitigated. Institutions should frame generative AI as a tool that supports thinking rather than replaces it, embedding critical evaluation and academic writing competencies into curricula to counterbalance the risk of overreliance and to safeguard the development of independent reasoning skills.

7. Conclusions, Limitations, and Future Work

7.1 Conclusions

This dissertation examined GenAI adoption in higher education in Cabo Verde using an extended UTAUT model that integrates classic acceptance determinants with GenAI-relevant variables, particularly Trust and Ethical Attitude. The results show that GenAI adoption is not explained only by utility and usability; it also depends on whether users feel the technology can be used responsibly in an academic context.

Regarding RQ1 (drivers of Intention and Use), the findings indicate that Behavioral Intention is positively associated with self-reported Use, which is consistent with the central UTAUT expectation that intention is related to behavior (Venkatesh et al., 2003). Behavioral Intention is mainly associated with Performance Expectancy, Hedonic Motivation, and Ethical Attitude. Effort Expectancy requires a cautious interpretation: its direct coefficient on Intention is negative and statistically significant, so the hypothesised positive direct effect is not supported. However, Effort Expectancy has a positive indirect association with Intention through Performance Expectancy, indicating that ease of use contributes to adoption mainly by increasing perceived usefulness. Social Influence does not significantly predict Intention in this model, suggesting that GenAI use in this context is more strongly associated with individual evaluations than with perceived social pressure.

Concerning RQ2 (value of the extended model), the results support the added explanatory relevance of the extension. Ethical Attitude captures legitimacy and responsible-use judgment, which directly shapes Intention. Trust plays an important upstream role, strengthening ethical acceptance and, indirectly, Intention. This configuration fits the GenAI reality in higher education, where uncertainty, integrity, and governance concerns are central rather than peripheral.

Regarding RQ3 (sentiment toward GenAI), the VADER-based analysis of translated open-ended responses indicates predominantly positive textual polarity (72.5%), suggesting optimism about GenAI's potential contribution to learning and productivity. However, this result should be interpreted as exploratory and descriptive because VADER is a lexicon- and rule-based method and does not replace interpretive qualitative analysis. The neutral/unclear (15.9%) and negative (11.6%) classifications, together with the content of the comments, point to continuing concerns about overreliance, reduced critical thinking, plagiarism, and responsible use. Taken together, these results suggest that positive expectations coexist with an ethical and trust-related filter, reinforcing the importance of governance, guidance, and AI literacy for responsible adoption.

This dissertation contributes empirically by providing evidence from a context that remains underrepresented in GenAI adoption research, which is still concentrated in larger or more frequently studied systems.

It contributes theoretically by showing that, in higher education, Trust may operate less as a simple “I will use it” belief and more as a condition that makes ethical acceptance possible—an important distinction when GenAI use intersects with authorship, assessment credibility, and academic values.

In practice, the results suggest that universities in Cabo Verde can promote more responsible adoption by focusing on clearly communicated academic use cases, ethical guidance, and enabling conditions such as training, access, and support.

7.2 Limitations

Several limitations should be considered. First, the data are cross-sectional and self-reported, which limits causal inference and may be affected by common method bias. Second, the sample is specific to Cabo Verde and the distribution of roles (students versus lecturers and staff) is unbalanced, which constrains generalisability and subgroup comparisons. Third, the model captures adoption intention and self-reported usage but does not measure learning outcomes, assessment performance, or long-term behavioural change. Finally, the sentiment analysis is exploratory and methodologically limited: VADER is mainly an English lexicon- and rule-based tool, the Portuguese responses had to be translated before scoring, and the method captures textual polarity rather than deep meaning, themes, irony, or contextual nuance. Therefore, the sentiment results should be interpreted only as complementary descriptive evidence.

7.3 Future work

Future research could adopt longitudinal designs to examine how Trust, ethical perceptions, and adoption intentions evolve as GenAI tools and institutional policies mature. Multi-group studies with more balanced samples, as well as cross-country comparisons, would help test the stability of the model across contexts. Further work could operationalise usage with richer behavioural measures (e.g., frequency and breadth of GenAI-supported tasks) and examine educational outcomes. Qualitative studies (interviews/focus groups) could deepen understanding of the conditions under which users perceive GenAI as ethically acceptable and pedagogically valuable.

References

Alotaibi, S. M. F. (2025). Determinants of Generative Artificial Intelligence (GenAI) adoption among university students and its impact on academic performance: The mediating role of Trust in technology. *Interactive Learning Environments*, *33*(6), 4159–4188. https://doi.org/10.1080/10494820.2025.2492785

Baig, M. I., & Yadegaridehkordi, E. (2025). Factors influencing academic staff satisfaction and continuous usage of generative artificial intelligence (GenAI) in higher education. *International Journal of Educational Technology in Higher Education*, *22*, Article 5. https://doi.org/10.1186/s41239-025-00506-4

Aparício, J. T., Aparício, M., Aparício, S., & Costa, C. J. (2024). Predicting the impact of generative AI using an agent-based model. *arXiv preprint arXiv:2408.17268*. https://doi.org/10.48550/arXiv.2408.17268

Committee on Publication Ethics. (2024). *Authorship and AI tools*. https://publicationethics.org

Correia, D. M. (2025). *Factors influencing the Use of generative artificial intelligence* [master's dissertation, ISEG – Lisbon School of Economics and Management]. University of Lisbon Repository.

Costa, C. J. (2025). Generative AI Models: A Comprehensive Review. *OAE – Organizational Architect and Engineer Journal*. https://doi.org/10.21428/b3658bca.d5d1872f

Costa, C. J., Aparício, M., Aparício, S., & Aparício, J. T. (2024). The democratization of artificial intelligence: Theoretical framework. *Applied Sciences*, *14*(18), Article 8236. https://doi.org/10.3390/app14188236

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., & Williams, M. D. (2023). So, what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities and challenges of generative AI. *International Journal of Information Management*, *71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, *21*(3), 719–734. https://doi.org/10.1007/s10796-017-9774-y

Fu, C. J., Silalahi, A. D. K., Huang, S. C., Phuong, D. T. T., Eunike, I. J., & Yu, Z. H. (2024). The (un)knowledgeable, the (un)skilled? Undertaking ChatGPT users' benefit–risk–coping paradox in higher education focusing on an integrated UTAUT and PMT. *International*

Journal of Human–Computer Interaction, *41*(9), 5663–5693. https://doi.org/10.1080/10447318.2024.2365028

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, *27*(1), 51–90. https://doi.org/10.2307/30036519

Granić, A. (2022). Educational technology adoption: A systematic review. *Education and Information Technologies*, *27*, 9721–9744. https://doi.org/10.1007/s10639-022-10902-7

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hutto, C. J., & Gilbert, E. (2014). VADER: A parsimonious rule-based model for sentiment analysis of social media text. Proceedings of the International AAAI Conference on Web and Social Media (ICWSM), 8(1), 216–225. https://doi.org/10.1609/icwsm.v8i1.14550

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255–260. https://doi.org/10.1126/science.aaa8415

Joshi, H. (2025). Integrating Trust and satisfaction into the UTAUT model to predict chatbot adoption: A comparison between Gen Z and millennials. *International Journal of Information Management Data Insights*, *5*(1), 100332. https://doi.org/10.1016/j.jjimei.2025.100332

Jovanović, J., & Campbell, M. (2022). *Generative artificial intelligence: Trends and implications*. Computer 55, 10 (Oct. 2022), 107–112. https://doi.org/10.1109/MC.2022.3192720

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Masrek, M. N., Baharuddin, M. F., & Syam, A. M. (2025). Determinants of behavioral intention to use generative AI: The role of Trust, personal innovativeness, and UTAUT II factors. *International Journal of Basic and Applied Sciences*, *14*(4), 378–390. https://doi.org/10.14419/44tk8615

McKnight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on*

Management Information Systems, *2*(2), Article 12. https://doi.org/10.1145/1985347.1985353

Organization for Economic Co-operation and Development. (2021). *OECD digital education outlook 2021: Pushing the frontiers with AI, blockchain and robots*. OECD Publishing. https://doi.org/10.1787/589b283f-en

Qi, K., Yunhong, G., & Changping, K. (2025). Bridging AI literacy and UTAUT constructs: Structural equation modeling of AI adoption among Chinese university students. *Humanities and Social Sciences Communications*, *12*, Article 1452. https://doi.org/10.1057/s41599-025-05775-y

Ray, P. P. (2023). ChatGPT: A comprehensive review on background, applications, and future directions. *Journal of Reliable Intelligent Environments*, *9*, 1–21. https://doi.org/10.1007/s40860-023-00205-5

Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.

Sullivan, M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. *Journal of Applied Learning and Teaching*, *6*(1), 31–40. https://doi.org/10.37074/jalt.2023.6.1.3

Tertiary Education Quality and Standards Agency. (2024). *Assessment reform for the age of artificial intelligence*. https://www.teqsa.gov.au

United Nations Educational, Scientific and Cultural Organization. (2021). *Artificial intelligence needs assessment survey in Africa*. UNESCO Publishing. https://unesdoc.unesco.org/ark:/48223/pf0000375322

United Nations Educational, Scientific and Cultural Organization. (2023). *Guidance for generative AI in education and research*. UNESCO Publishing.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. In *Advances in Neural Information Processing Systems* (pp. 5998–6008).

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and Use of information technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and Use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, *17*(5), 328–376. https://doi.org/10.17705/1jais.00428

Veiga, M., & Costa, C. J. (2024). Ethics and artificial intelligence adoption. *arXiv preprint*. https://doi.org/10.48550/arXiv.2412.00330

Verma, S., & Garg, N. (2023). Development and validation of techno-ethical orientation scale for Indian post-millennial students. *Journal of Science and Technology Policy Management*, *15*(6), 1294–1310. https://doi.org/10.1108/JSTPM-05-2022-0090

Zhao, L., Rahman, M. H., Yeoh, W., Wang, S., & Ooi, K.-B. (2024). Examining factors influencing university students' adoption of generative artificial intelligence: A cross-country study. *Studies in Higher Education*. Advance online publication. https://doi.org/10.1080/03075079.2024.2427786

APPENDICES

Appendix A - Questionnaire Applied

The questionnaire below was administered in Portuguese, the native language of the target population in Cabo Verde, to ensure comprehension and validity of responses. It was administered via Google Forms to understand the factors influencing the adoption of Generative Artificial Intelligence (GenAI) tools in the academic context in Cabo Verde. The instrument was developed based on the extended UTAUT model, incorporating the dimensions of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Trust, Hedonic Motivation, Ethical Attitude, Behavioral Intention, and Actual Use Behavior. Responses were collected anonymously and confidentially.

1 = Discordo totalmente 2 = Discordo 3 = Discordo ligeiramente 4 = Neutro 5 = Concordo ligeiramente 6 = Concordo 7 = Concordo totalmente

Dados Demográficos e Contextuais

1. Com que género se identifica? (Masculino / Feminino / Outra)
2. Qual a sua idade?
3. Em que universidade estuda ou trabalha? (Universidade de Cabo Verde; Universidade do Mindelo; Universidade de Santiago; Universidade Jean Piaget de Cabo Verde; Universidade Lusófona de Cabo Verde; Instituto Superior de Ciências Económicas e Empresariais; Instituto Superior de Ciências Jurídicas e Sociais; Escola Universitária Católica de Cabo Verde; Outra)
4. Qual é a sua função principal na universidade? (Estudante / Docente / Outra)
5. Qual é a sua área de estudo ou investigação principal? (Ciências Naturais; Ciências da Saúde; Engenharia e Tecnologia; Ciências Sociais e Económicas; Artes e Humanidades; Outra)

Expectativa de Desempenho (PE)

6. **PE1.** Considero as ferramentas de IA generativa úteis no meu dia a dia.
7. **PE2.** A utilização de ferramentas de IA generativa aumenta as minhas chances de realizar tarefas que são importantes para mim.

8. **PE3.** A utilização de ferramentas de IA generativa ajuda-me a realizar tarefas mais rapidamente.
9. **PE4.** A utilização de ferramentas de IA generativa aumenta a minha produtividade.

Expectativa de Esforço (EE)

10. **EE1.** Aprender a utilizar ferramentas de IA generativa é fácil para mim.
11. **EE2.** A minha interação com ferramentas de IA generativa é clara e compreensível.
12. **EE3.** Considero as ferramentas de IA generativa fáceis de utilizar.

Influência Social (SI)

13. **SI1.** As pessoas que são importantes para mim pensam que eu deveria utilizar ferramentas de IA generativa.
14. **SI2.** As pessoas que influenciam o meu comportamento consideram que eu deveria utilizar ferramentas de IA generativa.
15. **SI3.** As pessoas cujas opiniões eu valorizo preferem que eu use ferramentas de IA generativa.

Condições Facilitadoras (FC)

16. **FC1.** Tenho os recursos necessários para usar ferramentas de IA generativa.
17. **FC2.** Tenho conhecimento suficiente para usar ferramentas de IA generativa de forma eficaz.
18. **FC3.** Existe suporte técnico disponível para ajudar em dificuldades com o uso de IA generativa.

Confiança (TR)

19. **TR1.** Eu acredito que a IA generativa é eficaz e segura no que é desenhada para fazer.
20. **TR2.** Eu acredito que a IA generativa permite-me fazer o que eu preciso.
21. **TR3.** Eu acredito que os utilizadores de ferramentas de IA generativa são confiáveis.
22. **TR4.** Eu acredito que as ferramentas de IA generativa são desenvolvidas por organizações confiáveis.

Motivação Hedónica (HM)

23. **HM1.** É divertido para mim usar ferramentas de IA generativa.
24. **HM2.** As ferramentas de IA generativa são agradáveis/prazerosas de utilizar.
25. **HM3.** Sinto-me animada/o ao usar ferramentas de IA generativa.

Atitude Ética (EA)

26. **EA1.** Penso que usar ferramentas de IA generativa é aceitável.
27. **EA2.** Penso que usar ferramentas de IA generativa é ético.
28. **EA3.** Penso que usar ferramentas de IA generativa é certo.

Intenção Comportamental (BI)

29. **BI1.** Pretendo continuar a usar ferramentas de IA generativa no futuro.
30. **BI2.** Tentarei sempre usar ferramentas de IA generativa nos meus estudos/ensino.
31. **BI3.** Pretendo continuar a usar ferramentas de IA generativa com frequência.

Comportamento de Uso Real (UB)

32. UB1. Frequência de uso de ferramentas de IA generativa: (Nunca; Uma vez por mês; Várias vezes por mês; Uma vez por semana; Várias vezes por semana; Uma vez por dia; Várias vezes por dia)

Questão Aberta

Qual é a sua visão sobre o papel futuro da Inteligência Artificial Generativa no ensino superior em Cabo Verde? (resposta opcional, de natureza qualitativa)

Appendix B - Sample profile (N = 210)

Characteristic	Category	n	%
Gender	Female	150	71.4
	Male	60	28.6
Age group	≤20	66	31.4
	21–23	70	33.3
	24–26	24	11.4
	27–30	14	6.7
	≥31	36	17.1
Role	Student	189	90.0
	Lecturer	17	8.1
	Other staff	4	1.9
Field	Social and Economic Sciences	86	41.0
	Health Sciences	41	19.5
	Engineering and Technology	38	18.1
	Natural Sciences	26	12.4
	Arts and Humanities	19	9.0
University	Universidade de Cabo Verde (Uni-CV)	129	61.4
	Universidade do Mindelo (UM)	23	11.0
	Universidade de Santiago (US)	20	9.5
	Instituto Superior de Ciências Económicas e Empresariais (ISCEE)	15	7.1
	Universidade Jean Piaget de Cabo Verde (UniPiaget)	12	5.7
	Universidade Lusófona de Cabo Verde (ULCV)	5	2.4

Characteristic	Category	n	%
	Instituto Superior de Ciências Jurídicas e Sociais (ISCJS)	4	1.9
	Escola Universitária Católica de Cabo Verde (EU Católica)	2	1.0

Appendix C – GenAI use frequency (UB1; N = 210)

Frequency category	n	%
Several times per day	65	31.0
Several times per week	64	30.5
Several times per month	41	19.5
Once per week	13	6.2
Once per month	12	5.7
Once per day	11	5.2
Never	4	1.9

Appendix D – Cross-loading

	BI	EA	EE	FC	HM	PE	SI	Trust	Use
BI1	**0.887**	0.578	0.430	0.399	0.573	0.663	0.415	0.556	0.468
BI2	**0.910**	0.550	0.318	0.314	0.595	0.577	0.458	0.479	0.526
BI3	**0.941**	0.638	0.394	0.442	0.642	0.672	0.461	0.539	0.552
EA1	0.580	**0.853**	0.452	0.396	0.570	0.528	0.392	0.498	0.313
EA2	0.553	**0.899**	0.283	0.371	0.472	0.440	0.338	0.581	0.227
EA3	0.593	**0.918**	0.399	0.428	0.518	0.495	0.402	0.576	0.299
EE1	0.399	0.335	**0.900**	0.538	0.358	0.547	0.396	0.298	0.325
EE2	0.401	0.420	**0.900**	0.590	0.470	0.592	0.454	0.403	0.349
EE3	0.315	0.377	**0.881**	0.597	0.394	0.515	0.314	0.382	0.296
FC1	0.384	0.365	0.524	**0.860**	0.373	0.390	0.393	0.328	0.300
FC2	0.365	0.396	0.608	**0.866**	0.431	0.467	0.338	0.433	0.324
FC3	0.252	0.310	0.384	**0.659**	0.268	0.228	0.376	0.343	0.121
HM1	0.554	0.466	0.432	0.469	**0.868**	0.508	0.408	0.438	0.326
HM2	0.571	0.519	0.376	0.309	**0.911**	0.518	0.424	0.397	0.350
HM3	0.646	0.572	0.420	0.444	**0.905**	0.536	0.410	0.544	0.375
PE1	0.539	0.412	0.452	0.341	0.514	**0.787**	0.364	0.293	0.367
PE2	0.593	0.462	0.544	0.422	0.498	**0.861**	0.387	0.395	0.387
PE3	0.613	0.439	0.573	0.378	0.504	**0.836**	0.383	0.378	0.435
PE4	0.485	0.447	0.391	0.358	0.336	**0.716**	0.409	0.462	0.240
SI1	0.392	0.397	0.460	0.451	0.401	0.407	**0.887**	0.386	0.301
SI2	0.470	0.349	0.400	0.407	0.443	0.459	**0.927**	0.355	0.347
SI3	0.471	0.414	0.345	0.385	0.422	0.442	**0.926**	0.414	0.297
TR1	0.504	0.533	0.445	0.493	0.419	0.476	0.362	**0.827**	0.273
TR3	0.458	0.529	0.324	0.369	0.435	0.381	0.372	**0.878**	0.206
TR4	0.520	0.538	0.275	0.326	0.480	0.359	0.353	**0.874**	0.208
UB1	0.566	0.314	0.363	0.325	0.393	0.453	0.344	0.266	**1.000**