

Universiteit Leiden

Master ICT in Business and the Public Sector

A Novel Measurement of “AI Guilt”:
Exploring Its Influence on Student Behaviour and Generative AI Adoption

Name: Grigorios Krousiarlis
Student ID: 3476375
Date: 09/06/2026

Specialisation: Business

1st supervisor: Natalia Amat Lefort
2nd supervisor: Flor Plaza del Arco

Master’s Thesis in ICT in Business and the Public Sector

Leiden Institute of Advanced Computer Science
Leiden University
Einsteinweg 55
2333 CC Leiden
The Netherlands

A Novel Measurement of AI Guilt:
“Exploring Its Influence on Student Behaviour and Generative AI Adoption”

Abstract

As Generative AI tools become more common in higher education, it can be hard for students to distinguish the boundaries of acceptable usage and the expectations regarding their behaviour and performance. While prior research has largely examined Gen AI adoption through rational decision-making models, not much has been said for the role of morally grounded emotional responses that may shape how the students act. To address this gap, this study introduces and validates AI Guilt as a novel higher-order psychological construct that aims to reflect the feelings of guilt that arise when Gen AI tools are used in academic settings.

AI Guilt was conceptualized using established frameworks, drawing on Imposter Syndrome, Fear of Negative Evaluation, Attitudes Towards Plagiarism, and the remaining dimensions of the Theory of Planned Behaviour (Subjective Norms & Perceived Behavioural Control). Data was collected through an online survey, resulting in 158 valid responses. The relationships and structure were examined using Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM).

The findings support AI Guilt as a measurable and statistically valid construct. However, EFA showed that feelings of guilt about using Gen AI are connected in ways that aren't easy to separate, even though they are derived from distinct constructs. Structural Modeling showed that AI Guilt does not operate as a uniform mediator. Concerns about academic misconduct and ethics were linked to lower Behavioural Intention, while components related to perceived behavioral control were linked to higher Behavioural Intention. In turn, Behavioural Intention was a strong predictor of Actual “Gen AI” Use.

With this study, the aim is to contribute to theory by extending Gen AI adoption research beyond purely utility-based explanations and by demonstrating that morals and emotions in academic environments may function as behavioural regulators rather than just simple barriers. The importance of institutional clarity, AI Literacy support, and transparent guidance on acceptable Gen AI use to reduce ambiguity-driven discomfort and support responsible adoption is evident through the results.

Keywords: AI Guilt, Generative Artificial Intelligence, AI Ethics, Theory of Planned Behaviour, Academic Integrity, AI Literacy, Attitudes Towards Plagiarism, Imposter Syndrome

Introduction

In recent years, artificial intelligence (AI) and natural language processing (NLP) technologies, including ChatGPT, have gained prominence in academic settings, providing numerous advantages, from research aids to writing support. Even though these tools offer students unparalleled academic support (e.g., brainstorming, drafting, editing, and problem-solving), their use also introduces complex ethical dilemmas and psychological challenges.

At the heart of these challenges lies the emerging phenomenon of 'AI guilt' (also named 'AI shame' or ‘Technology Use Guilt'). It can be defined as the moral discomfort or inauthenticity experienced by people when using AI for tasks traditionally performed or expected to be performed by humans (Chan, 2024; Giray, 2024; Chee, 2023; Davis, 2023; Ziegelmayer & James, 2024). This feeling of guilt or shame is a significant trend, as evidenced by a recent industry survey, which suggested that 36% of Generation Z individuals (born after 1996) admit to experiencing guilt when using AI in the workplace (EduBirdie, 2024). This data, gathered from 2,000 Gen Z respondents in the US, highlights the widespread nature of this concern.

This discomfort often stems from fears of over-reliance and a perceived loss of originality when using AI tools for academic or work-related tasks. As Kasneci et al. (2023) suggest, people may perceive their work as "less genuine" when aided by AI. In essence, some students may struggle with the question of whether their academic achievements are truly their own. While existing research hints at the connection between AI guilt and psychological factors like imposter syndrome and fear of judgment (Chan, 2024; Ziegelmayer & James, 2024), empirical evidence on its impact on AI usage remains scarce. Notably, there is a lack of (i) established frameworks to measure AI guilt and (ii) studies exploring its influence on behavioural intentions and actual AI usage.

To address these gaps, this research develops and validates a novel framework to measure AI guilt and examines its influence on students' behavioural intentions and actual usage of generative AI tools (e.g., ChatGPT). By integrating the Theory of Planned Behaviour (TPB) with this new measurement, the study aims to provide a better understanding of student perceptions of AI technologies and the ethical dilemmas associated with GenAI adoption.

Drawing on survey data from 158 students, this study uses Structural Equation Modeling (SEM) to analyze the proposed relationships, aiming to answer the following research questions:

RQ1: How can AI Guilt in academic settings be conceptualized and measured as a multidimensional construct?

RQ2: How does AI guilt affect students’ Behavioural Intention to use Gen AI tools?

RQ3: To what extent does Behavioural Intention predict Actual Use of Gen AI tools?

The findings of this research have significant implications for educators, policymakers, and AI developers. By providing a validated measure of AI guilt, this study allows for more accurate investigations into the psychological impact of AI in education. Moreover, understanding the relationship between AI guilt and usage intentions can inform the development of ethical guidelines and educational interventions to mitigate negative psychological effects. This research aims to contribute to a deeper understanding of the evolving relationship between students and AI, helping to promote a more responsible and ethical integration of these powerful tools in academic settings. Ultimately, addressing AI guilt can ensure that AI technologies enhance, rather than undermine, the students' learning experience.

1. Literature Review

This section provides an overview of the definition, capabilities, and societal implications of Generative AI. Both the technological and institutional contexts are outlined in which psychological reactions like AI Guilt occur.

1.1 Definition of GenAI & Capabilities

Generative AI (GenAI) refers to systems that can generate original content such as text, code, images, and audio by getting trained on learning patterns from large-scale datasets through Neural Networks. (Vaswani et al., 2017) The Transformer architecture is fundamental to this capability, as it introduced attention mechanisms that replaced the traditional RNN-based methods (Recurrent Neural Networks) and enabled the model for context-aware learning. (Vaswani et al., 2017; Singh, 2024; Chapter 8 Attention and Self-Attention for NLP | Modern Approaches in Natural Language Processing, 2020)

Models like GPT-3 employ this architecture, featuring 175 billion parameters and enabling few-shot learning - a machine learning framework where the model learns how to make accurate predictions by training with limited labeled examples. (Brown et al., 2020) The latest GPT-4 introduced significant enhancements, featuring roughly 1.8 trillion parameters, incorporating multimodal capabilities, and enabling simultaneous processing of text and images. (OpenAI et al., 2023)

ChatGPT serves as the most established and remarkable example of generative AI, developed using architectures GPT-3 and GPT-4 by OpenAI. It is able to generate coherent and context-relevant responses through a statistical prediction of the next words. Other significant GenAI systems include Google's Gemini - formerly known as Bard, Antropic's Claude, and Meta's LLaMA. (Ozkaya, M. 2024; Singh, 2024)

Unlike early AI systems, such as rule-based programs or chatbots like ELIZA, GenAI is capable of handling very advanced and sophisticated tasks and calculations, such as writing essays, answering legal queries, tutoring in multiple languages, or generating scientific hypotheses in real time. (Adel et al., 2024). Despite this significant and remarkable leap, though, it has also been negatively received and raising ongoing ethical and reliability concerns (Stahl & Eke, 2023)

However, despite these extensive technical advancements, existing literature offers limited insight into how these capabilities interact with human psychological reactions or ethical self-perceptions, particularly in the academic context.

1.2 Evolution of AI's Role: from tool to Assistant/Collaborator

Generative AI has been a major shift in the field of education. The scope has expanded significantly beyond basic functions such as adaptive testing (GMAT, Khan Academy, Duolingo), plagiarism detection (Turnitin, Unicheck), grammar and syntax correction (Grammarly, Microsoft Editor), or paraphrasing (QuillBot). Currently, GenAI helps students in drafting essays, brainstorming, debugging code, refining their assignments, and ultimately transforming the learning process. (Erdawati et al., 2025; Zhai et al., 2024)

This marks a new era in human-computer interaction: from a tool, the role transforms to a collaborator. It can be described as moving from “AI for automation” to “AI for augmentation,” where AI extends human capabilities and supports learning in real time. For that, students need to be prepared to question and evaluate answers in an AI world. (Dignum, 2021) In short, students have transitioned from simply using tools to co-creating with AI tools, collaboratively deciding and negotiating in real time the outcome.

A representative example of this shift can be observed in the increasing reliance on ChatGPT (Capitalist, 2025). It is capable of assisting in drafting and refining writing (Bašić et al., 2023), offering real-time coding and debugging (Haque & Li, 2023), translating and paraphrasing text (Ho, 2023), etc.

These advanced capabilities introduce significant ethical and academic tension. Where does the student's effort end and AI assistance begin and end? The impact of GenAI can be compared to the introduction of calculators—initially disruptive, then eventually integrated. But unlike calculators, which primarily shifted how students handle numbers, GenAI reshapes how they think and communicate, making it harder to draw clear lines between human and machine effort and raising significantly deeper ethical and intellectual questions.

Using GenAI well now requires new thinking skills. Students must learn to evaluate and critically adapt AI outputs. In summary, GenAI functions as more than a conventional classroom tool but as an innovative teaching partner, reshaping how we design, experience, and assess learning.

This blurring of boundaries between human input and AI-assisted and eventually generated output introduces uncertainty in authorship and responsibility, which can trigger moral discomfort and internal conflicts, defined in this study as AI Guilt.

1.3 Societal Impacts of Generative AI

Generative AI is changing more than just how students learn, but it is also reshaping communication, work, and the way knowledge is created across all industries. Tools like GitHub Copilot, Notion AI, and ChatGPT are being used for coding assistance, reporting and forecasting, customer support, task automation, and brainstorming. (Scoble-Williams et al., 2024) According to McKinsey’s survey, 88% of organizations are using GenAI in at least one business area, especially in marketing, sales, software engineering, and development. (Singla et al., 2025)

However, these developments are not limited to productivity gains. It comes with significant concerns. The World Economic Forum has reported that GenAI has the potential to create up to 97 million new jobs by 2025, but it may also displace 85 million, particularly in routine work. (Gregg, 2024)

In the field of education, as already mentioned, these concerns translate to questions regarding the way students are learning. If AI can write essays, summarize articles, and solve mathematical problems, what happens to student agency, originality, and critical thinking? Researchers are warning about the awareness LLMs seem to have. In reality, they do not genuinely understand the content, but they just predict word patterns, which can lead to superficial learning and even factual errors. (Yu et al., 2025)
GenAI also tends to exhibit biases and generate “hallucinations” - confidently incorrect responses. Models often reflect social biases like stereotypes or narrow views of world aspects and make up facts. All these issues raise questions over AI’s trustworthiness in academic and professional settings. (IBM; Rubio-Licht, 2025)

This is the reason experts are teaching AI literacy and encouraging dialogue around it, meaning not just how to use the tools but also to understand their limits. (Floridi et al., 2018) It is important that users develop a cognitive framework to decide when to trust them, how to critically evaluate their outputs, and how to make choices over proceeding with or rejecting what they have generated.

These concerns extend beyond technical limitations and highlight the need to understand how individuals psychologically process concepts like trust, responsibility, and ethical use when interacting with Gen AI tools.

1.4 Global Institutional Readiness for Generative AI in Education

GenAI is transforming education globally. It evolves as part of the digital ecosystem at an uneven speed, as the rate of its adoption is influenced by the available local infrastructure, the regulations in place, and, of course, the culture of each country. Wealthy countries like Singapore and the United States are at the lead in adopting its advancements rapidly. However, at the same time, lower- and middle-income countries lag due to language constraints and lower institutional readiness as a result of digital access gaps across their educational systems. (Oxford Insights, 2025)

Singapore has initiated an AI literacy program in schools and universities, while the United States is including GenAI in the curriculum through student experimentation and private platforms. (AI Singapore and the United Nations Development Programme Collaborate to Close the AI Literacy Divide & Transform Communities in Developing Countries, 2025; McDonald et al., 2025; Ellis, 2024) Across Europe, countries are more cautious and conservative regarding GenAI. The UK was the first to formally categorize “undisclosed use of AI in coursework” as malpractice, requiring students to work under their teachers’ supervision, while some of France's top universities banned ChatGPT usage or even enforced no computer use at all. (Chazan, 2025; ACODS UK, 2023; Reuters, 2023; Morin, 2025; Busby, 2023; AI Use in Assessments: Your Role in Protecting the Integrity of Qualifications - JCQ Joint Council for Qualifications, 2025)

In the Netherlands, the universities of Utrecht and Rotterdam’s Erasmus are working to establish guidelines for Generative AI. (Utrecht University, n.d.; Erasmus University, n.d.) Utrecht permits supervised AI usage, while Maastricht University set in place a Generative AI policy in late 2024. (Maastricht University, 2024) Additionally, the government released "Government-wide vision on generative AI,” which emphasizes the increasing yet alarming adoption of GenAI in education, alongside its risks, similar to the annual report of the World Economic Forum. (World Economic Forum, 2025; World Economic Forum, 2025; Ministerie van Algemene Zaken, 2024)

On the other hand, countries of the southern part of the globe are facing even greater challenges. Even though educators from Africa and Southeast Asia are expressing interest in AI-supported learning, their countries still rank poorly in AI readiness. (Oxford Insights, 2026)

The culture of each country is another significant determinant of how AI is going to be shaped. In collectivistic cultures such as China (IDV=20), Japan (IDV=46), Turkey (IDV=37), or Greece (IDV=35), students may be more sensitive to the opinions and the attitudes of their peers or their faculty, making subjective norms a stronger predictor of AI Guilt or avoidance of adopting a behaviour such as using GenAI tools. In contrast, in the Netherlands (IDV=80) or the USA (IDV=90), students are more likely to act independently, depending on their own judgement, hence, subjective norms would become a less dominant factor when it comes to adopting GenAI. (Hofstede, n.d.; Hofstede, 2011; Mai Nguyen, 2015)

These differences throughout the world highlight how important it is to design and introduce AI tools as well as regulations in a way that is appropriate locally. If we don't, we risk making the digital gap even bigger by providing advanced tools to students who are already in a more advantageous position due to the geography or wealth of their country

1.5 Institutional Ambiguity and Regulatory Gaps in GenAI Adoption

Even though GenAI tools like ChatGPT are becoming widespread, most educational institutions, schools, and universities have not created clear rules or support systems to guide the students and the faculty staff. The 2024 UNESCO survey found that less than 10% of universities and schools had formal guidelines about GenAI in place. (UNESCO, 2023). In the absence of clear institutional guidelines, acceptable use of Gen AI is often left open to interpretation.

Major universities like MIT and Oxford have slowly created relevant guidelines, usually allowing the use of GenAI tools for brainstorming and editing but not for submitting work that has been generated completely by GenAI as their own. (MIT, 2025; University of Oxford, n.d.) They consider it fraud and will hold students who exercise this accountable for what they submit. They also warn about always verifying the generated output in terms of content, text, and the existence and accuracy of the citations. Even with these rules, though, enforcing them is hard, and it is not exactly clear how strict they should be, as the assessor is the one to evaluate whether the intended competences have been acquired.

The EU is developing a legal framework called the AI Act, which ranks AI tools by risk level. (European Commission, 2024) In the field of Education, GenAI is generally seen as “limited risk” but still requires transparency and clarification on how this can be done properly - how and when to disclose AI use and good data practices. The only exception seen as “high risk” is when it can determine access to education and later career paths. (European Commission, 2024)

Nowadays, a large proportion of individuals have heard the term "AI" or "ChatGPT." Despite the increasing adoption, concerns about the reliability and trust persist both in public and academic discussions. (Gillespie et al., 2023; Woolcock, 2025; Duarte, 2025; Edelman, 2025) Teachers are particularly concerned about students misusing it and earning its trust due to its ease of use and access and ending up letting it replace the established meaningful learning experience. (Fearn, 2024).

2. Generative AI in Academic Settings

2.1 How Learning is changing through GenAI

GenAI tools like ChatGPT are being heavily used nowadays by students in both undergraduate and postgraduate programs, changing the conventional approaches to homework. These tools are being used more and more for brainstorming, structuring essays, translating and simplifying academic sources, grammar and syntax checking, and coding. For non-native speakers, particularly, the most often used tools are for brainstorming, paraphrasing, text refinement, and lately, humanising AI-generated content. (Woolcock, 2025; Julie Jargon, 2025; Gruenhagen et al., 2024)

According to a global student survey, 86% of students are frequently using ChatGPT for their academic assignments. (Digital Education Council, 2024) Time efficiency, struggles with academic writing, and a lack of understanding of specific topics were mentioned amongst the most common motives behind it. It is also important to mention that many students highlighted their use of AI as a learning tool. (Baek et al., 2024)

These evolving behaviours suggest that students are redefining the limits of academic work rather than only cheating. Students who will employ AI typically view it as a “writing collaborator” rather than a content generator. (Dwivedi et al., 2023; Ryan et al., 2025) The concepts of authorship and intellectual ownership are therefore being questioned as these technologies are being involved.

2.2 Lack of a Unified Perspective on GenAI from Education’s side

Even though students have quickly embraced tools like ChatGPT for their academic workload, the case is not the same for the teachers and professors, whose reaction was not unified at all. (Mowreader, 2024) The division is wide, and there is no single approach across academia. Some teachers worry that if students use AI, they might cheat or submit work that is not entirely theirs, which could make it hard to evaluate whether the student deserves the grade/pass or, even more, whether the student actually knows. (Ruediger, D. et al., 2024) Others, however, see GenAI tools as a chance to teach students new technical skills like prompt engineering and to increase their critical thinking when it comes to understanding and judging AI-generated content - “AI literacy”. (Opesemowo, 2025; Kim et al., 2025; Woo et al., 2025)

According to a study examining the trust educators show in GenAI, a teacher’s view on AI often depends on the academic subject they teach, how high their perceived control over AI tools is, and whether their school or university encourages and supports them to understand what responsible AI use is. (Lyu et al., 2025; Ruediger, D. et al., 2024) In STEM subjects like engineering, mathematics, and computer science, educators are generally more accepting of these tools. They view them as assistive technologies for writing code, solving equations, and debugging. At the same time, professors in subjects like literature, philosophy, or sociology are more skeptical. Some worry that during usage, the student might copy too much and plagiarise, lose their personal writing style, and become less skilled at brainstorming, reasoning, and creativity. (Ruediger, D. et al., 2024)

Due to the fact that each academic field has a different perception of AI, students receive mixed signals. One professor might allow AI use, while another might be completely opposed to it.

A survey of 116 research universities in the USA showed that only less than half 41% provided syllabus statements on GenAI, indicating that explicit instructions on good practices and limitations remain mostly uncertain. (McDonald et al., 2025) That means most students are left in the dark over whether they can make use of tools like ChatGPT, what the limits are, and what the consequences would be in case they do. This inconsistency creates ambiguity in expectations regarding acceptable AI use. (Weale, 2025; New York Institute of Technology, 2023; Gannon, 2024)

Some professors are exploring new ways to include GenAI in teaching. For example, asking students to evaluate how good or bad an AI-generated essay is and provide comments for improvement. (Goode et al., 2025; Jonathan S. Jones, 2023; Samuel, 2025) The goal is to teach students how to use it responsibly and effectively without relying on it to do all the work. These creative teaching strategies encourage students to think critically about their usage and how to be honest about it. However, such approaches are still rare and not yet widely adopted across institutions. (Flaherty, 2025) As these tools become a regular part of education, universities and schools must teach teachers how to use these technologies and how to update their grading and feedback methods in order to remain fair and relevant.

2.3 Confusion Amongst Students

Despite increasing adoption of Generative AI, institutional guidance remains fragmented and inconsistent across educational contexts - only less than 10% of universities and schools had formal guidelines in 2024. (UNESCO, 2023) Of those that did, policies ranged from outright bans to allowing it under very strict conditions, requesting students to be honest, use it ethically, and always disclose it. (Xiao et al., 2023)

Due to the lack of clear rules, students rely on guessing what is okay. They might go by what their friends and classmates are doing or advice shared behind the scenes, a concept called “hidden curriculum,” meaning students are learning how to use AI but not through an officially designed teaching way. The confusion created leads to stress, and that is even more intense for those who care about doing the right thing but also feel the pressure to save time or keep up in competitive classes. (Mowreader, 2024)

The non-existence of a unified regulation or framework also leads to unfairness, as students in different subjects, institutions, or countries are not treated equally. (Xiao et al., 2023) International students or those who did not grow up with the education systems of the West might find it harder to know what is allowed. (Bannister et al., 2024) In collectivistic cultures, where group values are more important than individual ones, students tend to do what their peers do instead of following vague university rules. (Hofstede, 2011) So, using GenAI is not just a matter of whether it is allowed or not it depends heavily on what classmates are doing, where the student comes from culturally, and also how confusing the university’s position is. The decision ends up becoming a socially negotiated one rather than just a technical or ethical decision

These inconsistencies in institutional guidance contribute directly to students’ feelings of uncertainty, moral conflict, and even guilt around the usage of GenAI.

2.4 Redesign of Assessment and Plagiarism Check Methods

As GenAI tools become part of everyday student work, institutions are starting to worry about fair assessment design and academic integrity. The traditional plagiarism software, which focuses on

copying someone else's words, does not really apply when AI generates "original" text based on user prompts from scratch. Due to the fact that LLMs do not copy existing content but rather generate fresh ones, many detection tools fail to flag AI-generated text. In response to that, some institutions have updated their integrity check procedures to include unauthorized AI use as a violation. Others emphasise transparency, encouraging students to cite any AI contribution. For example, the University of Augusta recommends declaring AI use in the same way they would mention Grammarly, EndNote, or other tools. (Augusta University, 2024)

But even with these rules in place, it is inconsistent. AI detectors like Turnitin and GPTZero have low reliability and high false-positive rates. (Fowler, 2023; Liang et al., 2023) This is risky for some students who may be wrongfully accused or, on the other hand, wrongfully rewarded for using AI in an undetected way. In both cases, the system fails to address the purpose of real learning.

Several experts say institutions should redesign their assessment methods rather than follow punishment-based approaches. In-class writing, oral exams, reflections on AI outputs, or collaborative assignments that include both human and AI-generated elements are some of the suggestions. (Cassidy, 2024; Khlaif et al., 2025; Sullivan et al., 2023) They focus on how students learn and not just what they hand in. Yet these approaches remain rare, especially in large classes or places with strict/standardized curricula.

It is obvious that AI tools are evolving much faster than institutions can respond, widening the gap even more and leaving students with feelings of confusion and guilt as they are trying to learn in a system that has not kept up with their academic experience and how they actually study and work today.

3. Theoretical Framework

This section presents the Theoretical Framework of this study. It combines established psychological concepts with the Theory of Planned Behaviour in order to explain students' use of Generative AI tools in academic settings. More particularly, this research proposes the concept of AI Guilt as a multidimensional construct that embodies the emotional and ethical conflicts that students experience when interacting with Generative AI.

The following subsections describe the role of key psychological constructs and define the proposed research model and hypotheses.

3.1 Emotional and Psychological Implications of GenAI Use in Students

While a growing body of literature addresses regulations and redesign of assessment methods for GenAI, but few have focused on its effects on students' emotional and psychological well-being. Early studies show that AI use triggers a range of reactions, including relief from writer's block (Tica & Krsmanović, 2024), anxiety over being ethical (Jo, 2024), guilt about reduced authorship (Jo, 2024), fear of being caught, judged, or punished (Dangol et al., 2025), etc.

These emotions are not trivial. They shape how students experience their capacity to learn and their perception of themselves as students. For instance, students with high achievement aspirations or prior experience with academic shame, even authorized AI use, might feel like they are "cheating" even if the university allows it. (Woolcock, 2025)
AI may also amplify some existing students' problems already defined as psychological constructs:

- Imposter Syndrome, by making students feel like the relevant tool or algorithm did the work and they do not deserve their success. (Chan, 2025)
- Fear of Negative Evaluation, as students hide AI use from their peers and their professors (Chan, 2025)
- Moral Dissonance: In some cultures with strict perceptions on authorship, students might feel bad about doing something like using AI tools, even if it is technically allowed. (Chan, 2025; Woolcock, 2025)

These struggles can have real effects on learning engagement, satisfaction, and motivation, as well as trust in the education system. If these feelings are left unaddressed, they may lead to disengagement or selective avoidance of AI tools, which can exacerbate educational inequalities, benefiting some students while disadvantaging others. (Chow, 2025)

A significant empirical gap remains between what universities say, how students act, and how they actually feel. (Chan, 2025) This gap is not yet fully explored, and this thesis directly aims to address it through the introduction of AI Guilt as a measurable construct.

3.2 The significance of Psychological Factors in the adoption of GenAI

As the adoption of GenAI tools such as ChatGPT, Gemini, Claude, etc., in academic settings sees a rapid increase, understanding the emotional and psychological states and experiences of students becomes more essential. Despite the many discussions on the technological capabilities and regulatory frameworks in recent literature, there is a lack of empirical research examining the

students' perceptions of employing these tools, particularly in high-stakes contexts like academia, where academic integrity and self-concept/self-view/self-awareness are at risk.

Students' reactions to the use of AI often reveal confusion and anxiety, feelings of self-doubt, and ethical dilemmas. Technology acceptance frameworks (like TAM) or policy compliance models cannot purely address this complex situation. (Chan, 2024) Such behaviours can be shaped by notions including guilt, social pressure, fear of being judged, and concerns over authorship and ownership. An increasing number of academics argue that, as generative AI undermines traditional models of learning and authorship, it is necessary to also investigate the subjective psychological experience that comes with it (Cotton et al., 2023).

Furthermore, reactions like guilt may intervene in the "Behavioural Intention" - "Actual Use" gap. Students might plan on using GenAI tools but hesitate due to fear of negative evaluation or, alternatively, may actually use them and afterwards experience guilt, minimizing their satisfaction or sense of ownership of their efforts and work.

Understanding this emotional aspect as a complementary dimension to the technology is important in order to establish more ethical and supportive educational settings, as well as for developing predictive models of technology adoption that go beyond practical and functional benefits like saving time or money, enhancing efficiency, etc. In essence, in order to understand and predict AI use more effectively, especially in sensitive domains such as education, it is necessary to include in the equation the emotional, social, and psychological factors (like guilt, fear of judgment, social pressure, self-image, or ethical concerns), rather than solely focusing on the usefulness or the ease of use. (Ajzen, 1991; Dietvorst et al., 2014;, Chan, 2024)

3.3 Attribution Tendencies & Self-Serving Bias as Broader Psychological Background

Attributional tendencies may also play a significant role in shaping how individuals interpret their own actions, their outcomes, and their responsibilities, and in our case, these cognitive patterns may also influence the students' reactions to GenAI use.

Amongst the most established of these tendencies is the self-serving bias, which refers to a pattern where people attribute positive outcomes to their own abilities and qualities (internal causal explanation), while attributing failures or morally questionable actions to situational factors beyond their control (external causal explanation). This bias reflects a consistent motivational drive to maintain a favorable self-image and good self-esteem by selectively assigning causality, a fundamental concept of the Attribution theory. (Heider, 1958; Miller & Ross, 1975) As GenAI becomes more and more a part of our lives, these attributional tendencies may affect how students understand the results of work done with the contribution/involvement of AI.

In the academic context, this bias supports the students' efforts to maintain a positive sense of self, particularly when their academic performance falls short of expectations. However, the introduction of GenAI complicates this attribution process: when strong academic output is produced with AI involvement, students find it difficult to fully internalize success while still feeling personally accountable for the ethical ambiguity of using such tools. This mismatch disrupts the typical self-serving bias pattern and creates extra uncertainty around authorship, ownership, and responsibility. Together, this complexity is setting a broader psychological context, helping to

illuminate why emotional reactions such as discomfort and guilt are becoming increasingly important to examine

3.4 Proposing AI Guilt as a Multidimensional Psychological Construct

This research proposes AI Guilt as a multidimensional latent construct that captures students' internalized emotional unease associated with the use of Generative AI tools in academic settings. Rather than being directly observable, AI Guilt is conceptualized as an underlying psychological construct that is manifested through multiple measurable dimensions. Although guilt has been extensively examined in moral psychology as an emotional reaction to perceived ethical breaches (Baumeister et al., 1994), its relevance to human-AI interactions in the domain of education is relatively new and unexplored. AI Guilt particularly occurs in contexts where AI-generated content blurs the limits between assistance and authorship, leading students to wonder the extent to which their work reflects their own effort and competence. (Davis, 2023; Baume, 2013; Fritz, 2025)

To empirically validate this construct, the study examines whether the following dimensions significantly load into the underlying latent variable of AI Guilt through Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA):

- Imposter Syndrome: The belief that one's success is unearned, even in the presence of clear achievements. (Leary et al., 2000; Clance & Imes, 1978)

- Fear of Negative Evaluation: The anxiety of potential negative judgment from others concerning the use of GenAI tools. (Leary, 1983)

- Attitudes Towards Plagiarism: Personal moral position regarding the compatibility of GenAI tools use with academic integrity. (Ajzen, 1991; Ehrich et al., 2015; Pa, 2020)

- Subjective Norms (derived from the Theory of Planned Behaviour): Perceived social pressure from peers and educators over the use of GenAI tools. (Ajzen, 1991)

- Perceived Behavioural Control (derived from the Theory of Planned Behaviour): Beliefs regarding one's capability and control over the use of GenAI tools. (Ajzen, 1991)

All together, these components explain how students may encounter guilt even in the absence of formal rules against GenAI tools or any official statement of discouragement regarding their use by institutions. This framework allows for measuring AI Guilt in research and exploring how it influences students' behaviour and emotions. (Leary et al., 2000; Clance & Imes, 1978; Leary, 1983; Ehrich et al., Pa, 2020, 2015; Ajzen, 1991)

H1: AI Guilt is a multidimensional latent construct significantly reflected by Imposter Syndrome, Fear of Negative Evaluation, Attitudes Towards Plagiarism, Subjective Norms & Perceived Behavioural Control

Additionally, AI Guilt is expected to negatively influence students' Behavioural Intention to use Gen AI tools:

H2: AI Guilt negatively affects the Behavioural Intention (BI)

3.5 Imposter Syndrome

One of the primary psychological mechanisms contributing to AI Guilt is Imposter Syndrome, a phenomenon where high-achieving individuals perceive their success as undeserved and unearned and experience anxiety about eventually being exposed as frauds (Clance & Imes, 1978). This phenomenon, usually studied in relation to professional accomplishments and academic performance, is becoming more and more relevant in AI-enhanced educational settings.

When students are employing GenAI tools to do, improve, or correct their assignments, they may encounter a disconnection from the feeling of authorship/ownership. Regardless of the final output reflecting their own revisions and instructions, the perception of "an algorithm performing the hardest part" may occur and create feelings of inauthenticity. (Draxler et al., 2023) Students with imposter feelings are more prone to discrediting themselves for their own accomplishments in such contexts, especially if external tools or support systems contributed to their final product. (Whetsel, 2023)

In academic settings where creativity, constant hard work, and personal voice are highly valued, this is very present. (Chee, 2023) In these contexts, even acceptable use of AI may trigger feelings of impostor syndrome, particularly when the student is receiving praise or high grades. (Seran et al., 2025) Such experiences may result in an ongoing pattern of self-doubt, excessive perfectionism, procrastination, and avoidance of engagement—characteristics of the imposter syndrome (Chakraverty, 2020; Nosta, 2025).

Imposter syndrome (including AI Imposter Syndrome) may also correlate with demographic factors. Research shows that first-generation college students, women, and underrepresented minorities are more prone to feeling like impostors in academic settings (Hamm, 2024; Cokley et al., 2024; Price et al., 2024). In technology-related disciplines such as computer science, women have specifically reported higher levels of imposter syndrome and related performance anxiety (Rosenstein et al., 2020). Therefore, addressing the emotional impact of GenAI tools use is a bigger challenge that goes beyond the education domain. If their use increases imposter feelings more in already underserved groups, then failing to support them fairly can broaden existing gaps in confidence, participation/inclusion, and the need for additional support, making it a social equity issue.

Thus, Imposter Syndrome is expected to negatively affect students' intention to use Gen AI tools while also being examined as part of the measurement structure of AI Guilt:

H3: Imposter Syndrome (IS) negatively affects the Behavioural Intention (BI)

3.6 Fear of Negative Evaluation

Another catalytic factor of AI Guilt is the Fear of Negative Evaluation, an established psychological construct introduced by David Watson and Ronald Friend in 1969. (Watson, D. ,1969) Fear of Negative Evaluation refers to the distress or anxiety individuals experience when anticipating judgment or disapproval from others (Leary, 1983). In the academic context, students may fear being viewed as lazy, dishonest, or overly reliant on technological help if they admit their use of GenAI tools, even when such use is authorized/allowed.

Research has shown that students who experience fear of being judged (aka Fear of Negative Evaluation) are more likely to keep their academic struggles to themselves, avoid asking for help or collaborating, hesitate to interact and engage during classes, and try to prove themselves by working harder than necessary (Weeks et al., 2005). In the context of GenAI tools usage, this could mean that

students choose to hide the fact that they used them, avoid talking about it with classmates or educators, or feel the need to redo assignments that were created with the contribution of AI-generated content in order to feel like the work is truly their own.

These reactions are often triggered by confusion within the academic community and the universities themselves. When the rules regarding the GenAI tools' usage are unclear or vary between faculties, students rely on perceived norms, in other words, they proceed with what they believe others expect them to do. (Mowreader, 2024; Stone, 2024; Langreo, 2025) This gets especially important in cultures where the harmony of the total group matters a lot (collectivist cultures) or where authority is rarely questioned (high power distance cultures) because going against what is seen and perceived as the norm in these environments can lead to heavy judgment or social stigma (Arrindell, 2003)

As a result, Fear of Negative Evaluation is considered an important dimension within the measurement structure of AI Guilt by making more intense the social and reputational risks associated with the use of GenAI tools even regardless of the absence of any potential penalties.

Therefore, Fear of Negative Evaluation is expected to negatively influence students' intention to use GenAI tools:

H4: Fear of Negative Evaluation (FNE) negatively affects the Behavioural Intention (BI)

3.7 Attitudes Toward Plagiarism & Subjective Norms

Even though universities and educational institutions have official rules about what is considered plagiarism, students often rely on their personal belief systems and sense of what is right or wrong to judge what is acceptable, especially when it comes to grey areas like using AI tools. Research has shown that students who strongly disapprove of plagiarism are also less likely to accept behaviours like using ChatGPT or AI to get help with assignments. (Farooq & Sultana, 2021; Huang et al., 2025) They see these tools as a "shortcut," another way of cheating, being lazy, or being dishonest.

There is a new subfield of research - sometimes called "AI-giarism" - that suggests that students draw the line differently. (Chan, 2024) Many think copy-pasting AI-generated content as it is is wrong, while some feel that using AI for brainstorming or rephrasing/paraphrasing things is more acceptable. (Huang et al., 2025) So, if a student personally believes that using AI is the equivalent of cheating, they are very likely to experience feelings of guilt, even if the university has not banned it.

Thus, Attitudes Toward Plagiarism are expected to affect students' intention to use GenAI tools through AI Guilt:

H5: Attitude Towards Plagiarism (ATP) negatively affects the Behavioural Intention (BI).

Meanwhile, Subjective Norms, a construct from the Theory of Planned Behaviour refer to the social pressure/the perceptions of social expectations - whether their peers or teachers view a behaviour as acceptable or expected from them. (Ajzen, 1991) If students become aware of their teachers' or peers' disapproval of AI tools' use, they are more likely to avoid using them, not solely due to the rules but because they need and want to fit in. In case they don't comply and go against what they think others expect, they may feel guilt, especially in academic environments where conforming to norms is important. Social pressure doesn't only affect what students do - it also shapes the way they feel. If they use AI in a way that they think others would disapprove of, they might feel morally wrong, and

that's the point where the guilt will start getting shaped. (Husain et al., 2017) The strong influence these social and emotional dynamics hold highlights the need for clear, consistent academic policies around AI use so students are not left guessing what is right and what is wrong, and feelings of guilt and fear of negative evaluation can be better managed.

Accordingly, Subjective Norms is expected to negatively influence students' intention to use GenAI tools.

H6: Subjective Norms (SN) negatively affect the Behavioural Intention (BI).

3.8 Perceived Behavioural Control

Perceived Behavioural Control, a core construct from the Theory of Planned Behaviour, is a psychological concept that describes how capable someone feels they are in order to perform an action in certain conditions. (Ajzen, 1991) In this case, it refers to a student's belief in their ability to use AI tools in academic settings, and the conditions could be the university's regulations over AI use, the time pressure, the access to technology, the familiarity with the tools, etc.

In utilizing tools like ChatGPT, this includes confidence in controlling not only one's behaviour - using the tool strategically, ethically, with transparency- but also the technology itself -being familiar with the user interface of the subject tool, being able to write effective and accurate prompts, anticipating and adjusting the quality and the content of the output to suit their needs, being able to detect mistakes and inaccuracies, etc.

Students with higher Perceived Behavioural Control - higher confidence and control, might use AI tools to help them initiate brainstorming, revision of their own input, etc., and know how to direct them and tweak the output to reflect their thinking. They view these tools as assistive technology rather than a "shortcut", therefore, they feel no guilt about it because they don't perceive it as cheating. They are in charge and transparent, thus they do not experience guilt or shame. This has been confirmed by studies: students who received training in prompt engineering report higher "AI self-efficacy" (meaning confidence over handling AI) (Woo et al., 2025; Bewersdorff et al., 2024)
On the contrary, students with low Perceived Behavioural Control may feel that using AI tools is counterproductive, worrying that they cannot manage the tools effectively or feeling uncomfortable with the output, as they perceive it as artificial or not original. Research into AI adoption in higher education finds that when students feel they are in control, they are more likely to use AI properly - the key role of Perceived Behavioural Control shapes not just the intention but also the quality of the actual use. () This adds more specifically over time as students gain the Perceived Behavioural Control - for example, through training or practice. (Polyportis, 2024) They use AI more and more and start feeling less anxious about it. It is not just about the ethics but also the comfort and the emotional distress. (Mekheimer, 2025; Iraola-Real et al., 2023)
On a similar note, tech research links technological self-efficacy with reduced anxiety: students who feel confident with any technology used in education, not just AI, tend to use it more effectively, with less stress, and avoid unethical shortcuts. This connects everything to autonomy and ethics. If students believe they control what AI does, rather than blindly follow whatever is generated by it, they feel more ownership over the work they are submitting and worry less about cheating. (Nekrasova, 2024)

Thus, Perceived Behavioural Control is expected to positively affect students' intention to use GenAI tools:

H7: Perceived Behavioural Control (PBC) positively affects the Behavioural Intention (BI).

3.9 Research Gap

Despite GenAI's constant transformative impact on higher education, we still know very little about how students feel when using these tools. Most of the existing literature has primarily focused on the technical aspects, such as the accuracy and reliability of AI tools (Qu & Wang, 2025), concerns over academic integrity (Cotton et al., 2023; Bin-Nashwan et al., 2023), and the reactions of academic institutions (Fütterer et al., 2023), including implications for the traditional system, policy enforcement, and adaptation to the emerging technological new reality. However, the impact of emotional and moral factors like guilt, social influence, and ethical reasoning on students' decisions to use AI remains understudied. (Chan, 2024) This gets to be more and more relevant when the use of AI becomes morally ambiguous, for example, when using ChatGPT for brainstorming yet feeling guilty or adopting AI for academic purposes without any clear rules or guidance in place from the institutions. (Chan, 2024)

Therefore, this research aims to address this gap by introducing AI Guilt as a new, multidimensional emotional construct rooted in the student experiences, defined by five interrelated feelings-subcomponents: Imposter Syndrome, Fear of Negative Evaluation, Attitude Towards Plagiarism, Subjective Norms, and Perceived Behavioural Control. Together, these elements help explain why students may feel conflicted about using AI even when it is not explicitly prohibited.

In addition, the study extends the Theory of Planned Behaviour by integrating these psychological constructs into a single model for understanding GenAI use in academic settings, allowing us to explore - beyond what conventional Technology Acceptance frameworks already do - not just whether students use AI but why they choose to do so or not based on their inner beliefs and their perception of behaviours.

The outcome is a survey/framework that can be used to assess both students' Behavioural Intention and Actual Use of AI tools in academic settings.

This framework will be able to provide both theoretical and practical inputs. Theoretically, the model links technology adoption models with the emotional experience of AI use, which is often overlooked in GenAI research. Practically, the framework can offer a scalable diagnostic tool based on the Theory of Planned Behaviour and validated emotional constructs that can be used by researchers, educators, or policymakers to identify the emotional barriers, to explain the ethical interventions, and to promote more responsible GenAI use in academic settings.

3.10 Integration of Concepts & Framework Development

The concept of AI Guilt adopts the Theory of Planned Behaviour (Ajzen, 1991) as the foundational theoretical framework. TPB has been widely used in research on Educational Technology to predict Behavioural Intention and Actual Use of various digital tools, learning systems, e-learning, and plagiarism detection software. (Chu & Chen, 2015; Uzun & Kilis, 2019; Cooper et al., 2016) According to the framework, our actions are shaped by three main factors (Ajzen, 1991):

- Attitude towards behaviour: the individual's positive or negative evaluation of performing a behaviour. (Ajzen, 1991)
- Subjective Norms: the perceived social pressure from others (e.g., friends, classmates, teachers). (Ajzen, 1991)

- Perceived Behavioural Control: the perception an individual has over their ability to perform the behaviour successfully. (Ajzen, 1991)

In the context of GenAI tools usage in academic settings, these constructs are especially relevant. Students form attitudes about AI based on the perceived amount of usefulness and fairness, internalize the subjective norms from peers, and measure the degree of behavioural control based on AI literacy and guidance from their institutions.

In line with the Theory of Planned Behaviour, students' Behavioural Intention is expected to predict their actual use of GenAI tools:

H8: Behavioural Intention (BI) positively affects the Actual Use (AU) of Gen AI tools.

However, TPB does not explicitly include any emotional factors/dimensions/elements, especially ones that have to do with moral topics such as guilt and shame, that play a critical role in academic settings. Therefore, this research proposes AI Guilt to extend TPB by incorporating the emotional and ethical tensions that may shape students' Behavioural Intention towards Gen AI use.

Constructing AI Guilt helps fill the gap of current models by focusing on students' emotional and ethical struggles when using AI. As developed earlier, AI Guilt is a multidimensional construct composed of the following:

- Imposter Syndrome (Leary et al., 2000; Clance & Imes, 1978)
- Fear of Negative Evaluation (Leary, 1983)
- Attitudes towards Plagiarism (Ajzen, 1991, Ehrich et al., Pa, 2020)
- Subjective Norms (Ajzen, 1991)
- Perceived Behavioural Control (Ajzen, 1991)

Instead of seeing guilt as just something that exists or not, this model suggests that AI Guilt may help explain variation in students' Behavioural Intention to use AI.

- A student who has a high intention to use AI tools but also experiences high levels of guilt may be hesitant to do so.
- A student with low guilt and high intention is more likely to translate his intention into actual use.

3.11 Research Model Visualization

Drawing from the hypotheses outlined in the previous sections, the following research model (Figure 1) is proposed. While the hypotheses above are derived from established theoretical constructs, the subsequent analysis adopts an exploratory character. Therefore, the final structure and tested relationships may differ from the initially proposed model.

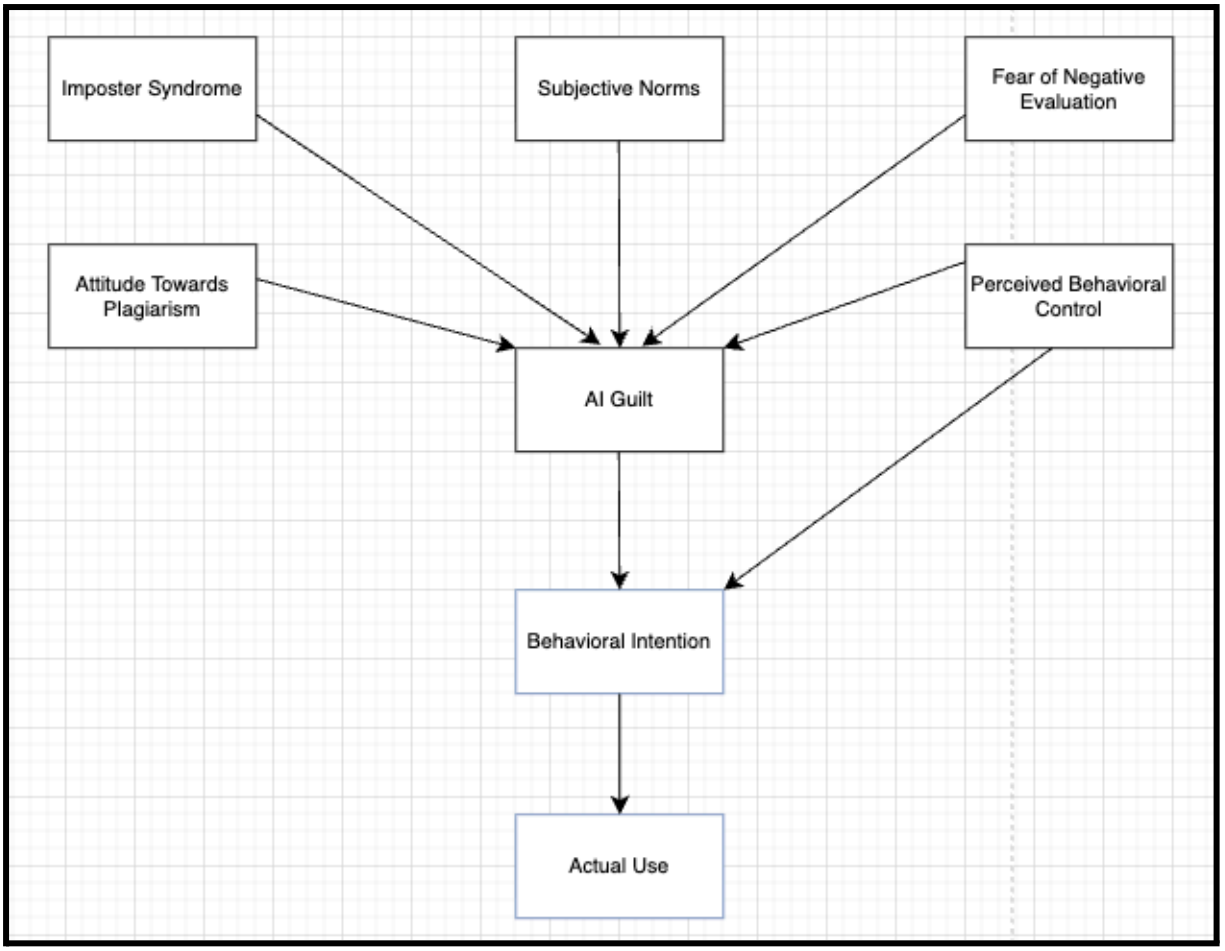


Figure 1. Theoretical Research Model

4. Methodology

The following section outlines the methodology employed to (1) build the survey instrument for assessing AI Guilt through the constructs used to define it, (2) validate the instrument's psychometric characteristics, and (3) analyze the relationship between AI Guilt, student Behavior, and the Acceptance and Use of Generative AI tools such as ChatGPT in academic contexts.

The survey instrument was built with the adoption of Churchill's (1979) framework for construct development and refinement and was further guided by the methodological principles proposed by Hinkin (1998). These models were selected due to their extensive use in behavioral and psychological research and their suitability in developing multidimensional concepts such as AI Guilt.

The latent construct of AI Guilt was initially conceptualized as consisting of four connected subconstructs:

- The Imposter Syndrome,
- Fear of Negative Evaluation,
- Attitudes Towards Plagiarism and,
- Subjective Norms & Perceived Behavioral Control, both derived from the Theory of Planned Behaviour (TPB)

The already validated instrument surveys were examined and adapted where necessary to suit the academic context and focus on the use of Generative AI tools. This involved the integration of items from the Impostorism Scale (Leary et al., 2000), Leary's Fear of Negative Evaluation Scale (1983), the preexisting plagiarism attitude questionnaire (Pa, 2020), and additional items that were created or adapted in order to assess the student's Behavioural Intentions and actual usage patterns of Generative AI tools, informed by the Theory of Planned Behavior (TPB).

Before full deployment, a pilot survey was conducted with a small group of students to assess the clarity, consistency, and validity of the items. Based on the feedback, the final version of the questionnaire was published, and 158 valid responses were collected. Following the data collection, Exploratory Factor Analysis (EFA) was conducted to enhance the measurement instrument by identifying and retaining only statistically relevant items as well as to look at how the constructs evolved and grouped into new constructs. The refined version was subsequently assessed by the Confirmatory Factor Analysis (CFA) in order to evaluate the reliability and convergent validity of the construct as well as the Cronbach's Alpha Reliability.

At last, Structural Equation Modeling (SEM) was used to examine the proposed correlations amongst the constructs. Structural Equation Modeling allows for simultaneous analysis of multiple dependent relationships for measurement error, making it ideal for the evaluation of AI Guilt's role as the mediator between psychological predictors and technology adoption behaviour.

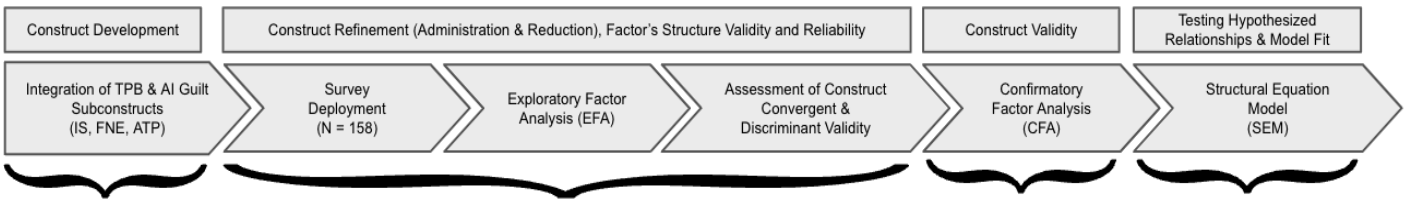


Figure 2. Overview of the Research Methodology Process

4.1 Sample Characteristics

The initial questions collected background information, including the age, the gender, the level of study, the primary academic discipline, previous exposure to Generative AI technologies, and the main contexts in which these tools were used (e.g., academic, personal, or professional). These question items were included to support descriptive analysis and exploratory examination of potential group level differences in AI Guilt and technology adaptation patterns.

		Frequency	Percentage
Age			
	18-25	46	29.1%
	26-30	59	37.3%
	31-35	38	24.1%
	> 35	15	9.5%
	Total	**158**	**100.0%**
Gender			
	Female	81	51.3%
	Male	76	48.1%
	Non-binary	1	0.6%
	Total	**158**	**100.0%**
Educational Level			
	High School Diploma or Equivalent (e.g., GED)	1	0.6%
	Some College, No Degree	9	5.7%
	Undergraduate/Bachelor's Degree (e.g., BA, BS)	70	44.3%
	Some Graduate School, No Degree	1	0.6%
	Master's Degree (e.g., MA, MS, MBA)	64	40.5%
	Doctoral Degree (e.g., PhD, EdD)	6	3.8%
	Professional Degree	5	3.2%
	Vocational/Technical Certification or Diploma	1	0.6%
	Other	1	0.6%
	Total	**158**	**100.0%**
Study Discipline			
	Arts & Humanities	30	19.0%
	Business/Economics	11	7.0%
	Engineering	26	16.5%
	Health Sciences	6	3.8%
	Science	26	16.5%
	Social Sciences	19	12.0%
	Technology	35	22.2%

Other	5	3.2%
Total	**158**	**100.0%**
Experience with GenAI tools		
No experience at all.	3	1.9%
Very little experience (I have only heard of these tools).	10	6.3%
Beginner (I have used these tools a few times).	36	22.8%
Intermediate (I use these tools occasionally for various tasks).	48	30.4%
Advanced (I use these tools regularly and am familiar with their capabilities).	51	32.3%
Expert (I use these tools extensively, and have a very in depth understanding of their functions)	10	6.3%
Total	**158**	**100.0%**
Frequency of usage of GenAI tools in the last month		
Never	15	9.5%
Rarely	14	8.9%
Sometimes	53	33.5%
Frequently	41	25.9%
Very Frequently	35	22.2%
Total	**158**	**100.0%**

Table 1 Sample Characteristics

Table 1 summarizes the demographic and academic characteristics of the final sample (N = 158), highlighting key variables such as age, gender, educational level, discipline/field of study, experience with Generative AI tools, and frequency of use during the last month. These attributes ensure the relevance and diversity of the sample in relation to the research's objective, which is to understand AI Guilt and its influence on student behaviour and adoption of such technologies.

Participants were mainly between the ages of 18 and 35, with the largest groups being 26-30 years old (58.0%) and 18-25 years old (46.0%). Gender distribution was relatively balanced, with 51.3% identifying as female and 48.1% as male. 84.8% of the respondents had either a bachelor's or master's degree, reflecting a well educated sample aligned with the academic settings of the study.

The most prevalent fields of study were Technology (22.2%), Arts & Humanities (19.0%), and Engineering/Science (each 16.5%). This diversity provides a broader view of how Generative AI tools are perceived and used across different domains.

In terms of Gen AI familiarity, over 60% of the participants rated themselves as either advanced (32.3%) or intermediate (30.4%) users. Only 1.9% reported no experience at all. Additionally, 33.5% of the sample reported using Generative AI tools at least "sometimes" in the past month, and 48.1% indicated they used these tools either frequently or very frequently, highlighting the increasing prevalence of Generative AI adoption in the academic context.

The inclusion of both new starters and expert users allows for a more comprehensive understanding of how AI Guilt may work across.

4.2 Questionnaire Development

The questionnaire for this study included demographic information and seven main sections: (1) Imposter Syndrome, (2) Fear of Negative Evaluation, (3) Attitudes Towards Plagiarism, (4) Subjective Norms, (5) Perceived Behavioral Control, (6) Behavioural Intention, and (7) Actual Use. All these together were combined in order to embody an original multidimensional construct, AI Guilt, and to examine its relationship with students' behavioural intentions and actual use of Generative AI tools in the academic context. All items were assessed on a five point Likert scale (1=Strongly Disagree to 5=Strongly Agree) unless stated otherwise.

The development of the questionnaire followed a construct driven adaptation approach (Churchill, 1979; Hinkin, 1998), in which items from validated/established psychological and behavioural instruments were rephrased and contextualized in order to reflect the academic use of Generative AI. Rather than creating entirely new items, the existing scales were modified to maintain the theoretical foundation while ensuring the applicability in terms of context.

4.1.1 Imposter Syndrome

The Imposter Syndrome construct was measured using items adapted from the Impostorism Scale developed by Leary et al. (2000). The original scale assesses feelings of intellectual fraudulence and fear of being exposed as less capable than others perceive. In this study, items were contextualized to reflect the use of Generative AI tools in academic settings.

For example, the original item *"I'm afraid people important to me may find out that I'm not as capable as they think I am"* was adapted to *"I am afraid that my teachers or peers may find out that I rely on ChatGPT or similar GenAI tools more than they expect."*

Similarly, *"In some situations I feel like a 'great pretender' that is, I'm not as genuine as others think I am"* was modified into *"In some situations I feel like a 'great pretender' when I submit work that was fully or partly made by ChatGPT or similar GenAI tools."*

These adaptations preserve the original construct's focus on perceived misrepresentation of competence while placing it specifically within the context of Generative AI assisted academic performance.

We expect individuals scoring high on Imposter Syndrome, to experience greater AI Guilt, particularly when they try to compensate for perceived skill deficiencies. These individuals may internalize the belief that using Generative AI tools exposes their "weaknesses," lowering their willingness to adopt such tools openly.

4.1.2 Fear of Negative Evaluation

The Fear of Negative Evaluation was measured using the brief version of the scale developed by Leary (1983). This construct captures the anxiety related to being judged or evaluated negatively by others. Items were adapted to reflect concerns about how the Use of Generative AI tools is perceived by instructors and peers.

For example, the original item "*I am afraid others will not approve of me*" was adapted into "*I am afraid other people will not approve of my use of ChatGPT or similar GenAI tools for academic work and learning."* This way, the original scale's emphasis on interpersonal evaluation is preserved while aligning it with the social and academic implications of Gen AI use.

We expect that students with high Fear of Negative Evaluation will show stronger AI Guilt and possibly lower Behavioural Intention to use Generative AI tools, especially when their academic environment lacks support and encouragement for such usage.

4.1.3 Attitudes Towards Plagiarism

In order to evaluate Attitudes Towards Plagiarism, items were derived from the questionnaire developed by Pa (2000), which measures ethical beliefs about academic dishonesty. Specifically, only the items with a negative connotation, "Negative Attitudes Towards Plagiarism" as defined, were retained and reworded to explicitly reference Generative AI content.

For example, the original item, "*In times of moral and ethical decline, it is important to discuss issues like plagiarism and self-plagiarism*," was adapted into "*In times of ethical uncertainty, it is important to discuss the responsible use of ChatGPT or similar GenAI tools,*" ensuring that the traditional concepts of plagiarism are extended to include emerging concerns associated with AI assisted authorship/ownership and disclosure of Gen AI tools usage.

Students with stronger Negative Attitudes Towards Plagiarism are expected to experience greater AI Guilt, especially when they use Generative AI tools without clear institutional guidelines disclosed. These students may be more cautious or ethically conflicted when it comes to their approach to AI assisted work.

4.1.4 Subjective Norms

The Subjective Norms construct, which actually constitutes Ajzen's Theory of Planned Behaviour (TPB), evaluates the perceived social pressure to perform or avoid a given behaviour.(1991) Items were rephrased to capture the influence of peers, instructors, and institutional policies on students' decisions to use Generative AI tools.

For example, the original TPB item "*Most people that are important to me think that I should/should not perform this behavior*" was adapted into "*Most people who are important to me think that I should use ChatGPT or similar GenAI tools for my studies,*" preserving this way the structure of the TPB subconstruct item while placing it within the academic context.

We expect that individuals who perceive strong social support for the use of Generative AI tools (e.g., higher Subjective Norms) will exhibit lower AI Guilt and greater intention to use such tools. On the contrary, those individuals who feel judged and unsupported may internalize more guilt and hesitations, leading to limiting adoption.

4.1.5 Perceived Behavioral Control

The Perceived Behavioral Control dimension was also adapted from the Theory of Planned Behaviour and reflects the students' confidence in their ability to use Generative AI tools effectively and responsibly. (Ajzen, 1991)

For example, the original item "*Whether or not I perform this behavior is entirely up to me*" was adapted into "*Whether or not I use ChatGPT or similar GenAI tools is entirely my decision,"* aligning this way the construct with students' perceived autonomy and self efficacy in engaging with Generative AI tools.

We expect that individuals with higher Perceived Behavioral Control will show both greater Actual Use of Generative AI tools and lower levels of AI Guilt, as confidence in managing such tools may alleviate uncertainty, shame, or fear related to their usage.

4.1.6 Behavioural Intention

Behavioural Intention was measured using four items adapted from prior technology adoption and Theory of Planned Behaviour based studies (e.g., Ajzen, 2000; Davis, 1989). These items captured students' planned future use, willingness to recommend Generative AI tools to others, and likelihood of relying on AI when facing academic challenges.

For example, a standard intention item like "*I intent to use this system regularly*" was adapted into "*I plan to use ChatGPT or similar GenAI tools regularly for my studies.*"

We expect that AI Guilt may act as a negative predictor of Behavioural Intention. The greater the guilt a student feels related to Generative AI tools usage, the less likely they are to intend to use these tools regularly, even if they are familiar with or have access to them.

4.1.7 Actual Use

The final part of the questionnaire measures the Actual Use as a behavioural outcome. Rather than relying solely on attitude indicators, two items assessed both the frequency of recent Generative AI use and the proportion of academic tasks supported by ChatGPT or similar tools. These items provided a quantitative estimate of real-world adoption of Generative AI tools in academic contexts.

We expect that higher Behavioural Intention and lower AI Guilt will predict greater Actual Use, completing the chain of influence in the research model from psychological constructs to real-world behavior.

4.2 Data Collection

The study employed a structured online questionnaire to measure the multidimensional AI Guilt construct and examine its influence on students' behavioural intentions and actual use of Generative AI tools.

The survey was published on the Qualtrics platform and distributed in spring 2025, initially via Leiden University's student channels and later via Amazon Mechanical Turk (MTurk). The target population

consisted of university students from various disciplines and educational levels across the country who speak the English language. Participants were instructed to reflect on their experiences and perceptions of Generative AI tools use in academic settings. In total, 183 responses were recorded, out of which 158 were valid following the exclusion of incomplete responses, attention check failures, and time thresholds.

To comply with ethical research standards, all participants were provided with an informed consent form before beginning the survey. Respondents were informed that their data would be used exclusively for academic purposes, handled confidentially, and stored securely.

4.3. Scale Refinement & Validation

The refinement and validation of the AI Guilt framework required a pair of two types of analysis. The first one involved, the Exploratory Factor Analysis (EFA), was used to examine the foundational structure of the construct's dimensions and help with the identification of the items that did not strongly align with their intended (initially designated) latent constructs. The second one involved is the Confirmatory Factor Analysis (CFA) in order to verify the resulting measurement model and to assess the reliability, the convergent validity, and the discriminant validity of the items.

This sequential approach was designed to ensure that the proposed AI Guilt construct embodied via the subdimensions of Imposter Syndrome, Fear of Negative Evaluation, Attitudes Towards Plagiarism, Subjective Norms, and Perceived Behavioral Control showed both theoretical consistency and empirical robustness before being incorporated into the structural model.

4.3.1 Exploratory Factor Analysis (EFA)

The first stage of the analysis required performing Exploratory Factor Analysis (EFA) to identify the latent factor structure of the proposed measurement model and to refine the instrument by removing items that did not load strongly onto their theoretically intended dimensions. The analysis was performed using IBM's SPSS 31st version.

Unlike traditional scale validation approaches that impose predefined factor groupings, this study adopted an exploratory approach, allowing the factor structure to emerge naturally from the data. This was particularly important given the novelty of the AI Guilt construct, which integrates psychological and behavioural dimensions not previously combined within a single measurement framework in the context of Generative AI use in academic settings.

In order to assess the suitability of the dataset for factor analysis, sample adequacy was checked using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. The results indicated strong factorability of the correlation matrix. The KMO value was 0.815, exceeding the recommended threshold of 0.70, which suggests that the sample size and the correlations between the different items were adequate for reliable factor extraction. Bartlett's Test of Sphericity was statistically significant (χ=1743.80, df=496, $p<0.001$), which confirms that the correlation matrix was not an identity matrix and that the variables were sufficiently correlated to justify factor analysis.

Factor extraction was performed using Principal Component Analysis with orthogonal rotation (Varimax) to optimize interpretability and minimize crossloadings amongst components. Factors were

kept according to eigenvalues exceeding 1.00 and visual inspection of the scree plot. Items with factor loadings below 0.60 or with substantial crossloadings on multiple factors were reviewed and removed to improve the construct. Exceptions were made for two items -with loadings 0.583 and 0.570- in order to avoid one item dimension, as this would cause issues later with the structural model

This refined solution revealed a multifactor structure that aligned closely with the theoretical framework, outlining the five subdimensions inherent to the AI Guilt construct. This allowed for a preliminary empirical evidence for the conceptual separation between internal psychological experiences (e.g., Imposter Syndrome and Fear of Negative Evaluation), ethical attitudes (Attitudes Towards Plagiarism) and social and control based influences (Subjective Norms and Perceived Behavioral Control.

4.3.2 Reliability & Discriminant Validity

The EFA evaluated the psychometric quality of the latent dimensions by examining the internal consistency and construct validity of each factor.

Internal consistency was examined using Cronbach's Alpha, with values of 0.70 or higher indicating acceptable reliability. The findings indicated significant variation across dimensions. The AI Guilt core dimension (C1), which integrates some items from Fear of Negative Evaluation and Imposter Syndrome, showed excellent internal consistency (α = 0.948), indicating strong coherence amongst its retained indicators. (C3) and (C5), which only used items from Subjective Norms and Fear of Negative Evaluation, also reached or were very close to the suggested level, with α values of 0.730 and 0.700, respectively. In contrast, the items for Attitudes Towards Plagiarism (C2), selected items from Subjective Norms (C4), Imposter Syndrome (C6), and Perceived Behavioral Control (C7) had lower alpha values between 0.549 and 0.628, showing moderate to weak internal consistency and suggesting that these areas might need more improvement in future studies.

Convergent Validity was assessed through the calculation of Composite Reliability (CR) and Average Variance Extracted (AVE). AVE values above 0.50 indicate that a dimension explains more than half of the variance in its observed indicators. The result revealed that the primary AI Guilt subconstruct (C1) achieved an AVE of 0.533, providing clear support for convergent validity. The remaining subconstructs did not meet the recommended AVE threshold, indicating limited convergent validity and highlighting potential conceptual overlap or items that are not strong enough. For example, Subjective Norms items forming subconstruct (C3) exhibited partial support with an AVE of 0.405, while items of Fear of Negative Evaluation forming subconstruct (C5) exhibited an AVE value of 0.350, suggesting that although indicators were related to their latent constructs meaningfully, a portion of variance remained unexplained.

Discriminant Validity was examined by comparing the square root of each subconstruct's AVE value with its correlations with other latent variables. This procedure ensures that each subconstruct shares more variance with its own indicators than with other subconstructs in the model.

Because several subconstructs yielded Cronbach's Alpha and AVE values below the commonly accepted thresholds, the internal consistency and convergent validity of these specific dimensions are limited. Consequently, any structural relationships involving these subconstructs should be interpreted with caution, and the corresponding measurement items may require refinement in future research.

4.3.3 Confirmatory Factor Analysis (CFA)

Following the identification of the factor structure by Exploratory Factor Analysis (EFA) on a subset of the data, a Confirmatory Factor Analysis was conducted in order to validate the dimensions of the AI Guilt construct and its related variables. The analysis employed Structural Equation Modelling (SEM) with IBM's AMOS v31 software. The model's fit to the data was evaluated using various fit indices, including the Comparative Fit Index (CFI), the Root Mean Square Error of Approximation (RMSEA), and the Chi-Square statistic to degrees of freedom ratio (χ^2/df). The standards for satisfactory model fit included a CFI value of 0.9 or above, an RMSEA value of 0.08 or less, and a χ^2/df ratio under 5. The dataset was randomly split into two subsets, with one used for EFA and the other for CFA, ensuring independent validation of the measurement model.

4.3.4 Structural Equation Modeling (SEM)

In the last phase of the analysis, SEM was employed in order to evaluate the proposed correlations. This means to integrate the response variables into the model, allowing the measurement of the influence of AI Guilt on Behavioural Intention and Actual Use of Generative AI tools. The assessment of the model's fit was dependent on the same metrics used previously: CFI, RMSEA, and χ^2/df ratio.

5. Results

The objective of this study was to develop and validate a new framework for assessing AI Guilt and its impact on students behaviour and their use of Generative AI tools. To accomplish this, an online survey was employed and distributed to students, resulting in 158 valid responses. To understand the different parts of the AI Guilt concept and its subcategories, a detailed scale development process was followed, in which the dataset was divided into two subsets: one for Exploratory Factor Analysis (EFA) to identify the underlying structure and one for the Confirmatory Factor Analysis (CFA) to validate the measurement model. The final scale captures the psychological and behavioral factors influencing Generative AI adoption in academic settings. It was developed using an empirical approach that led to the confirmation and establishment of key items from the five initial dimensions (Imposter Syndrome, Fear of Negative Evaluation, Attitudes Towards Plagiarism, Subjective Norms, Perceived Behavioral Control) as seven new ones.

5.1 Exploratory Factor Analysis (EFA)

The proposed construct of AI Guilt was examined using Exploratory Factor Analysis (EFA), and more specifically it involved Principal Component Analysis (PCA) with Varimax rotation and Kaiser normalization. Refining the measurement instrument by keeping just the most psychometrically strong items was the goal of it in order to find the underlying factor structure.

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.815, exceeding the recommended threshold of 0.7, and Bartlett's Test of Sphericity was significant ($\chi^2 = 1743.80$, $df = 496$, $p < .001$), indicating that the data were suitable for factor analysis. The EFA revealed seven factors with eigenvalues greater than 1, collectively accounting for approximately 59% of the total variance, suggesting that the assessed dimensions were well represented. Since the first principal component accounted for 34.81% of the total variance, which is below the commonly accepted 50% threshold for identifying Common Method Bias (CMB), suggesting that CMB was not a primary concern.

Strict criteria for item retention were as follows: (i) principal factor loadings <0.60, (ii) cross loadings <0.40, and conceptual fit with the intended construct items. This final instrument was cleansed of items that did not meet these criteria or had unclear loadings.

Table 2 Rotated Component Matrix. Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Items retained are indicated in a bold grey shade. The threshold is 0.60 with exceptions for the items indicated with dashed lines.

	1	2	3	4	5	6	7
ISY4	0.888	0.033	-0.091	0.071	-0.117	0.106	-0.087
ISY5	0.840	0.066	0.017	-0.018	-0.092	0.118	0.013
ISY2	0.839	0.155	-0.059	0.127	-0.113	0.169	-0.068
ISY3	0.814	0.128	0.126	-0.037	-0.101	0.068	-0.170
ISY1	0.798	0.090	0.164	0.032	-0.163	-0.082	-0.031
ISY7	0.794	-0.027	0.030	0.072	-0.126	0.247	0.047

FNE3	0.794	0.085	0.058	0.260	0.133	-0.097	0.080
FNE9	0.789	0.078	-0.236	-0.001	0.163	-0.116	0.014
FNE5	0.767	0.189	0.178	0.299	0.131	-0.160	-0.084
FNE11	0.758	0.270	0.032	0.129	0.249	-0.043	-0.196
FNE1	0.752	0.105	0.207	0.229	0.140	-0.218	-0.022
FNE8	0.738	0.287	0.033	0.279	0.109	0.011	-0.077
ISY6	0.726	-0.135	-0.328	-0.102	-0.152	0.264	-0.031
FNE6	0.700	0.299	0.091	0.328	0.039	-0.083	-0.191
FNE12	0.563	0.180	0.441	0.059	0.088	0.027	-0.154
ATP1	0.221	0.844	-0.053	0.084	-0.003	-0.031	-0.068
ATP3	0.318	0.797	-0.027	0.083	0.072	0.018	-0.142
ATP2	0.097	0.559	0.394	0.164	-0.376	0.157	0.139
ATP4	0.247	0.559	0.207	0.317	-0.487	0.031	0.065
PBC4	-0.062	0.105	0.839	0.155	0.046	0.053	0.210
PBC2	0.108	-0.103	0.712	-0.038	-0.235	0.199	0.031
SNO5	0.139	0.170	0.048	0.802	0.019	0.059	0.012
SNO3	0.418	0.193	0.079	0.677	0.078	0.013	0.021
SNO1	-0.030	-0.036	-0.031	0.180	0.822	0.129	0.098
SNO2	0.163	0.017	-0.072	-0.007	0.725	0.329	0.233
FNE7	-0.115	-0.064	-0.020	-0.132	0.244	0.783	0.221
FNE2	0.412	0.181	0.328	0.111	0.124	0.583	-0.036
FNE4	0.201	-0.200	0.205	0.469	0.096	0.570	-0.176
FNE10	-0.151	0.364	0.310	0.172	0.048	0.546	0.130
PBC3	-0.065	-0.068	0.224	-0.191	0.028	0.128	0.787
SNO4	-0.031	-0.006	-0.036	0.253	0.055	0.136	0.721
PBC1	-0.266	-0.068	0.086	-0.124	0.365	-0.161	0.633

Several adjustments were made to the tool according to the results of EFA, and the following structure emerged. The components were labeled based on the dominant conceptual theme reflected by the highest loading items within each factor, ensuring that each label resonates with the underlying psychological or behavioural dimension represented by the grouped items.

Component 1 - AI-Induced Self Doubt & Evaluation Anxiety

This main factor includes all elements of Imposter Syndrome (ISY1-ISY7) and most items from Fear of Negative Evaluation (FNE1, FNE3, FNE5, FNE6, FNE8, FNE9, and FNE11). Insecurities and self-criticism about using Generative AI tools are reflected in these items. The fear of being exposed academically is expressed by ISY1 ("I worry that using ChatGPT will make others question my academic abilities") and FNE9 ("I am usually concerned about how using ChatGPT affects other people's perception of my intelligence”). Item FNE12 (“I often worry that using ChatGPT or similar Generative AI tools will make me say or submit wrong things”) was excluded as it scored lower than 0.6

Component 2 - Ethical Attitudes Towards AI Use

Items ATP1 ("The use of ChatGPT-generated content should be disclosed") and ATP3 ("Using ChatGPT content without mentioning it is unethical") loaded clearly and produced a separate construct representing ethical concerns. Because of their modest loadings (<0.6), ATP2 and ATP4 were not included.

Component 3 - Perceived Autonomy and Learning Confidence

Items PBC2 (“Whether or not I use ChatGPT is entirely my decision”) and PBC4 (“Even if I struggle at first, I believe I can learn to use ChatGPT effectively”) formed this dimension, representing users’ autonomy and confidence in learning.

Component 4 - Institutional Norms (Restrictive)

Items SNO3 ("My professors encourage the use of ChatGPT") and SNO5 ("If my university restricted ChatGPT, it would affect my use") grouped together, representing perceived encouragement or discouragement from academic institutions.

Component 5 - Social Norms (Encouraging)

Items SNO1 ("Most people who are important to me think I should use ChatGPT") and SNO2 ("My friends/classmates use ChatGPT") loaded together, capturing perceived pressure or influence from tight social circles.

Component 6 - Social Judgment Indifference

FNE2, FNE4, and FNE7 were loaded together, although the last two fell slightly below the standard threshold (0.583 & 0.570, respectively). They were retained as an exception, though, in order to avoid a one item component. These items tap into fear about mistakes or poor outcomes when using Generative AI tools. "I often worry that using ChatGPT will make me say or submit wrong things" (FNE7) is only one example of how these items reflect these feelings. FNE10 did not make the cut, as it failed to meet the minimum factor loading threshold and did not load significantly onto any component.

Component 7 - AI Competence & Peer Adoption

A hybrid component indicating perceived AI Competence & Peer Adoption over behavior was produced by PBC1 ("I am confident in my ability to use ChatGPT"), PBC3 ("I have access to resources"), and SNO4 ("If my professors discouraged its use, it would negatively impact my decision").

As a result of the Exploratory Factor Analysis, the original theoretical constructs were reorganized into empirically derived components (C1-C7). Consequently, the structural relationships tested in the following analyses are based on these combined components rather than the initially proposed individual constructs.

Appendix A and Table 2 provide a comprehensive list of the items that were deleted and those that were retained, together with the factor loadings for each. Appendix B contains the initial questionnaire with all items as part of their intended dimension.

5.2 Discriminant Validity and Reliability

To evaluate the reliability and the construct validity of the newly established components measuring AI Guilt, we assessed each factor for internal consistency, convergent validity, and discriminant validity.

Composite Reliability (CR) was calculated for each of the seven components derived from the EFA and confirmed in the CFA. CR values above the commonly accepted threshold of 0.70 suggest satisfactory internal consistency. Amongst the components, the first one, C1 -consisting of all Imposter Syndrome items and the majority of items from Fear of Negative Evaluation- achieved a high CR value of 0.948, indicating excellent internal reliability. Other components like C3 - Perceived

Autonomy and Learning Confidence and C5 - Social Norms (Encouraging) delivered moderate CR values (0.716 and 0.751, respectively). The rest of the components scored lower than the threshold.

Average Variance Extracted (AVE) was also calculated to assess convergent validity, with the recommended threshold here being 0.50 or higher. Again, the primary component C1 - AI-Induced Self Doubt & Evaluation Anxiety exceeded this benchmark with an AVE of 0.532, indicating that its items collectively explain more than half of the variance in the underlying structure. Other components like C3 - Perceived Autonomy and Learning Confidence and C5 - Social Norms (Encouraging) did not approach acceptable levels, with AVE values lower than the threshold (0.405 and 0.349, respectively), suggesting weaker convergent validity. However, if the AVE is less than 0.50 but the Composite Reliability is higher than 0.6, the Convergent Validity of the construct is still considered acceptable, which applies to both C3 - Perceived Autonomy and Learning Confidence and C5 - Social Norms (Encouraging). Notably, for components C2 - Ethical Attitudes Towards AI Use, C4 - Institutional Norms (Restrictive), C6 - Social Judgment Indifference, and C7 - AI Competence & Peer Adoption, Convergent Validity was not supported.

Table 3 Factor Loadings & Reliability/Validity Metrics

Item	Component	Factor Loading
FNE6	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.818
ISY6	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.612
FNE8	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.72
FNE1	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.766
FNE11	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.812
FNE5	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.819
FNE9	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.723
FNE3	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.801
ISY7	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.711
ISY1	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.736
ISY3	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.733
ISY2	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.815
ISY5	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.728
ISY4	C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.756
ATP2	C2 - Ethical Attitudes Towards AI Use	0.645
ATP1	C2 - Ethical Attitudes Towards AI Use	0.723
SNO3	C4 - Institutional Norms (Restrictive)	0.898
SNO5	C4 - Institutional Norms (Restrictive)	0.64
PBC2	C3 - Perceived Autonomy and Learning Confidence	0.718
PBC4	C3 - Perceived Autonomy and Learning Confidence	0.634
SNO2	C5 - Social Norms (Encouraging)	0.737
SNO1	C5 - Social Norms (Encouraging)	0.632
FNE4	C6 - Social Judgment Indifference	0.805
FNE2	C6 - Social Judgment Indifference	0.714
FNE7	C6 - Social Judgment Indifference	0.491
PBC1	C7 - AI Competence & Peer Adoption	0.395

SNO4	C7 - AI Competence & Peer Adoption	0.616
PBC3	C7 - AI Competence & Peer Adoption	0.606

Table 4 Cronbach's Alpha & Composite Reliability Metrics

Component	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.948	0.949	0.533
C2 - Ethical Attitudes Towards AI Use	0.622	0.638	0.313
C3 - Perceived Autonomy and Learning Confidence	0.730	0.751	0.405
C4 - Institutional Norms (Restrictive)	0.628	0.639	0.314
C5 - Social Norms (Encouraging)	0.700	0.716	0.350
C6 - Social Judgment Indifference	0.549	0.555	0.226
C7 - AI Competence & Peer Adoption	0.625	0.628	0.306

Discriminant Validity was assessed using the Fornell and Larcker (1981) criterion, which requires that the square root of the AVE for each factor be greater than its correlations with other constructs. In this analysis, full discriminant validity could not be confirmed across all factors due to overlapping conceptual domains

In summary, the results suggest that the core construct of AI Guilt, and more particularly the primary dimension C1 - AI-Induced Self Doubt & Evaluation Anxiety, has strong psychometric properties. However, the remaining smaller behavioral dimensions should be interpreted with care because their convergent validity is either borderline or not sufficient. These findings will be revisited in the Structural Model Analysis to determine the overall robustness of the measurement framework.

5.3 Confirmatory Factor Analysis (CFA)

To further validate the structure of the AI Guilt construct, a second Confirmatory Factor Analysis (CFA) was conducted. The model included the newly proposed components, seven in total (C1-C7).

The model fit indices for the initial model indicated an overall poor fit. For the default model, the Chi Square value was $\chi^2(329) = 632.880$, which gives a CMIN/DF ratio of 1.924, which falls within the commonly accepted range of acceptable model fit (between 1 and 3). The Comparative Fit Index (CFI) was 0.746, which falls below the commonly acceptable threshold of 0.90 and therefore indicates a poor fit. While a CFI of 0.746 is below the traditional threshold, such fit indices are not uncommon during the initial exploratory stages of a complex, multidimensional novel construct like AI Guilt. Therefore, the model was retained for further structural testing, with the acknowledgment that the measurement model requires refinement. The Root Mean Square Error for Approximation (RMSEA) was 0.096, with a 90% confidence interval between 0.085 and 0.107, indicating a relatively high level of approximation error, consistent with the complexity of the model and the number of indicators.

Even though the overall fit indices were not very high, the standardized factor loadings for the items that were kept were usually very high. For example, all items in Component 1 (AI-Induced Self Doubt & Evaluation Anxiety), which combined Imposter Syndrome and Fear of Negative Evaluation items, had loadings above 0.70. For example, FNE5 (.819), FNE6 (.818), ISY2 (.815), and FNE3 (.801) all had loadings above 0.70. which means they were all consistent with each other.

However, Discriminant Validity was not fully established. This occurred especially for the items in the first component (C1 - AI-Induced Self Doubt & Evaluation Anxiety), where items of Imposter Syndrome and Fear of Negative Evaluation were not clearly separable. This overlap was supported by relatively high correlations (e.g., C6 - Social Judgment Indifference <–> C7 - AI Competence & Peer Adoption = .777, C2 - Ethical Attitudes Towards AI Use <–> C3 - Perceived Autonomy and Learning Confidence = .566, C1 - AI-Induced Self Doubt & Evaluation Anxiety <–> C3 - Perceived Autonomy and Learning Confidence = .556) between latent items and further validated by overlapping thematic interpretations during the construct development.

In short, the CFA shows that the majority of the proposed constructs demonstrate acceptable convergent validity and can be used in the next phase, which is the Structural Equation Modeling (SEM) testing. However, future research should focus on refining overlapping items and improving the discriminant validity to enhance the overall model fit.

5.4 Structural Equation Modeling (SEM)

As established in the EFA, the original theoretical constructs were reorganised into empirically derived components (C1-C7). Therefore, the structural relationships tested in this section are based on these components rather than the initially proposed constructs.

After checking the measurement model with Confirmatory Factor Analysis (CFA), several refinement rounds guided by the Modification Indices (MI) took place to build the final Structural Equation Model (SEM) to confirm the suggested relationships between the concepts in the AI Guilt Model. Figure 3 illustrates the full model tested, which includes latent variables derived from the data-driven components identified during Exploratory Factor Analysis (EFA).

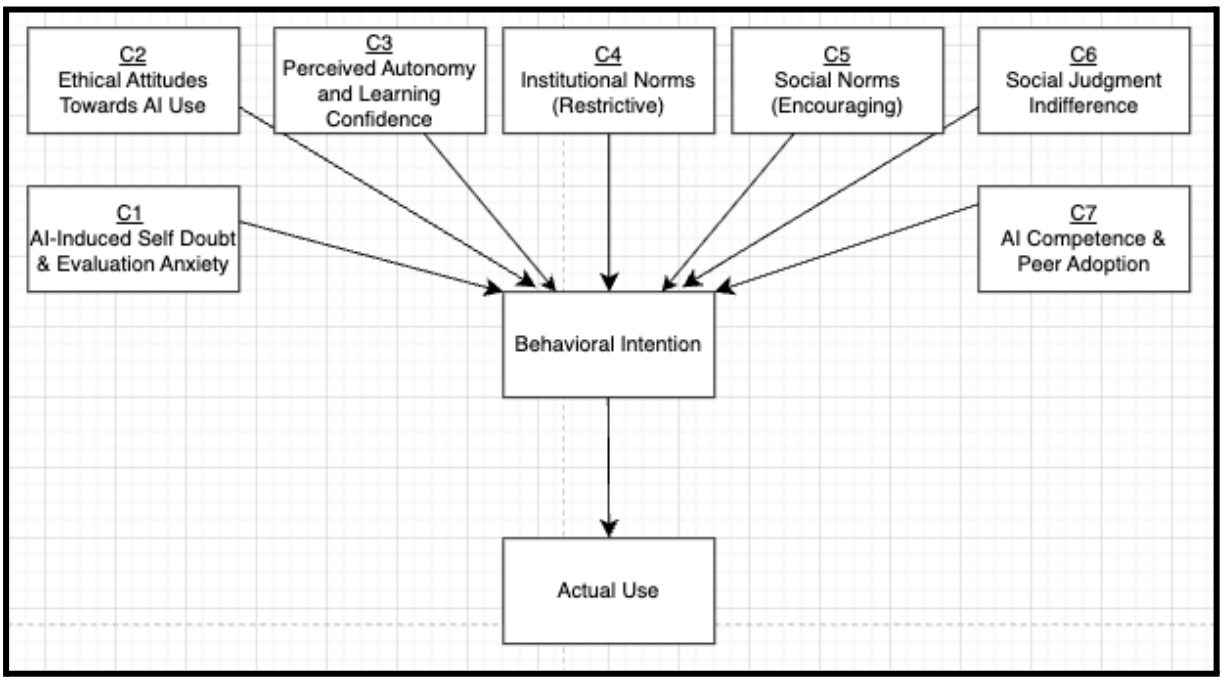


Figure 3. Empirical Research Model

The model demonstrated an acceptable to good overall fit. The chi-square value was $\chi^2(431) = 706.956$ ($p < .001$), which gave a CMIN/DF ratio of 1.640, which is an acceptable level of model parsimony. The Comparative Fit Index (CFI) was 0.904, and the Tucker Lewis Index (TLI) was 0.889, which means that both were within the range of adequate to good fit. The RMSEA was 0.064 (with a 90% confidence interval of [0.055, 0.072]) with a PCLOSE value of 0.005, suggesting that the model's

structure is good. All values are within the recommended thresholds (CMIN/DF <3, CFI > 0.900, RMSEA < 0.08).
SEM tested the influence of the empirically derived components (C1-C7) on Behavioural Intention (BI) and Actual Use (AU). In standard SEM reporting, $p < 0.05$ is considered statistically significant, $p < 0.01$ is highly significant, and $p > 0.10$ is not significant. Table 5 summarizes the hypotheses testing results derived from SEM, and below it, hypothesized effects and findings are discussed.

Table 5 Summary of Hypotheses Testing Results

Hypothesis	Relationship Tested	Support
H1	AI Guilt is a multidimensional construct reflected by C1-C7	Partially Supported
H2	AI Guilt → Behavioural Intention (BI)	Not Supported
H3	AI Self-Doubt & Evaluation Anxiety (C1) → Behavioural Intention (BI)	Not Supported
H4	Social Norms (Encouraging) (C5) → Behavioural Intention (BI)	Not Supported
H5	**Ethical Attitudes Towards AI Use (C2) → Behavioural Intention (BI)**	**Supported**
H6	Social Influence Components (C4, C5) → Behavioural Intention (BI)	Not Supported
H7	**Control-related Components (C6, C7) → Behavioural Intention (BI)**	**Supported**
H8	**Behavioural Intention (BI) → Actual Use (AU)**	**Supported**

H1: AI Guilt is a multidimensional latent construct significantly reflected by C1-C7

The measurement model findings indicate that AI Guilt is not a unidimensional construct but consists of multiple components (C1-C7) identified through EFA and validated through CFA. However, the observed cross-loadings and mixed composition of factors suggest that the construct is complex and not distinctly separable across dimensions. Therefore, H1 is partially supported, as the construct exists but does not exhibit a perfectly distinct factor structure.

H2: AI Guilt → Behavioural Intention (BI)

AI Guilt, as a latent construct, was reflected through components (C1 - C7), which demonstrated mixed effects on Behavioural Intention. While some components such as C2 - Ethical Attitudes Towards AI Use had a strong negative effect ($\beta = –.598$, $p = .013$), others like C5 - Social Norms (Encouraging), C6 - Social Judgment Indifference, and C7 - AI Competence & Peer Adoption all had positive effects. This pattern of inconsistency shows that **H2 is not supported**, since AI Guilt did not have a uniform negative influence on Behavioural Intention.

H3: AI-Induced Self Doubt & Evaluation Anxiety → Behavioural Intention (BI)

All of the ISY items (ISY1–ISY7) were loaded into C1 - AI-Induced Self Doubt & Evaluation Anxiety, which is part of the AI Guilt construct. However, since C1 - AI-Induced Self Doubt & Evaluation Anxiety didn't have a significant effect on BI ($\beta = .016$, $p = .839$), **H3 is not supported**.

H4: Social Norms (Encouraging) → Behavioural Intention (BI)

FNE items appeared in both C1 - AI-Induced Self Doubt & Evaluation Anxiety and C5 - Social Norms (Encouraging), both parts of the AI Guilt construct. C1 - AI-Induced Self Doubt & Evaluation Anxiety did not have a significant impact on BI ($\beta = .016$, $p = .839$), whereas C5 - Social Norms (Encouraging) had a significant positive effect ($\beta = .368$, $p = .042$). These results **don't support H4** because they go against the expected negative link.

H5: Attitudes Toward Plagiarism (ATP) → Behavioural Intention (BI)

C2 - Ethical Attitudes Towards AI Use contained only ATP items, and it significantly negatively affected BI (β = –.598, p = .013). Therefore, **H5 is supported**.

H6: Components reflecting social Influence (C4, C5) → Behavioural Intention (BI)

Items originally associated with Subjective Norms were reflected in two distinct components, C4 - Institutional Norms (Restrictive) and C5 - Social Norms (Encouraging). In addition, some related variance appeared in C6 - Social Judgment Indifference, which is conceptually distinct. The results indicate mixed effects on Behavioural Intention. C4 - Institutional Norms (Restrictive) demonstrated a positive but non-significant effect (β = .401, p = .061), whereas C5 - Social Norms (Encouraging) showed a statistically significant positive effect (β = .368, p = .042). These findings do not support the hypothesized negative relationship. Additionally, C6 - Social Judgment Indifference, which consists of Fear of Negative Evaluation items rather than social influence, exhibited a strong and significant positive effect on Behavioural intention (β = .777, p = .003). Therefore, **H6 is not supported**.

H7: Components reflecting Perceived Behavioural Control (C6, C7) → Behavioural Intention (BI)

Items reflecting PBC were found in C6 - Social Judgment Indifference and C7 - AI Competence & Peer Adoption, both within the AI Guilt construct. Both components significantly predicted Behavioural Intention, C6 - Social Judgment Indifference (β = .777, p = .003) and C7 - AI Competence & Peer Adoption (β = .434, p = .005), **supporting the hypothesis H7**.

H8: Behavioural Intention (BI) → Actual Use (AU)

BI significantly predicted Actual Use (β = .657, p < .001), confirming the behavioral link expected in the Theory of Planned Behaviour. That means that students who express a higher intention to use Generative AI tools are indeed more likely to engage with such tools in practice. Thus, **H8 is fully supported**.

Table 6 SEM Results: Impact of AI Guilt in Behavioural Intention and Actual Use

Relationship	Estimate	Std. Err.	p-value
BI ← C1 - AI-Induced Self Doubt & Evaluation Anxiety	0.016	0.079	0.839
BI ← C2 - Ethical Attitudes Towards AI Use	**-0.598**	0.241	**0.013**
BI ← C3 - Perceived Autonomy and Learning Confidence	-0.111	0.126	0.378
BI ← C4 - Institutional Norms (Restrictive)	0.401	0.215	0.061
BI ← C5 - Social Norms (Encouraging)	**0.368**	0.181	**0.042**
BI ← C6 - Social Judgment Indifference	**0.777**	0.258	**0.003**
BI ← C7 - AI Competence & Peer Adoption	**0.434**	0.154	**0.005**
Actual Use ← Behavioural Intention	**0.657**	0.090	**<0.001**

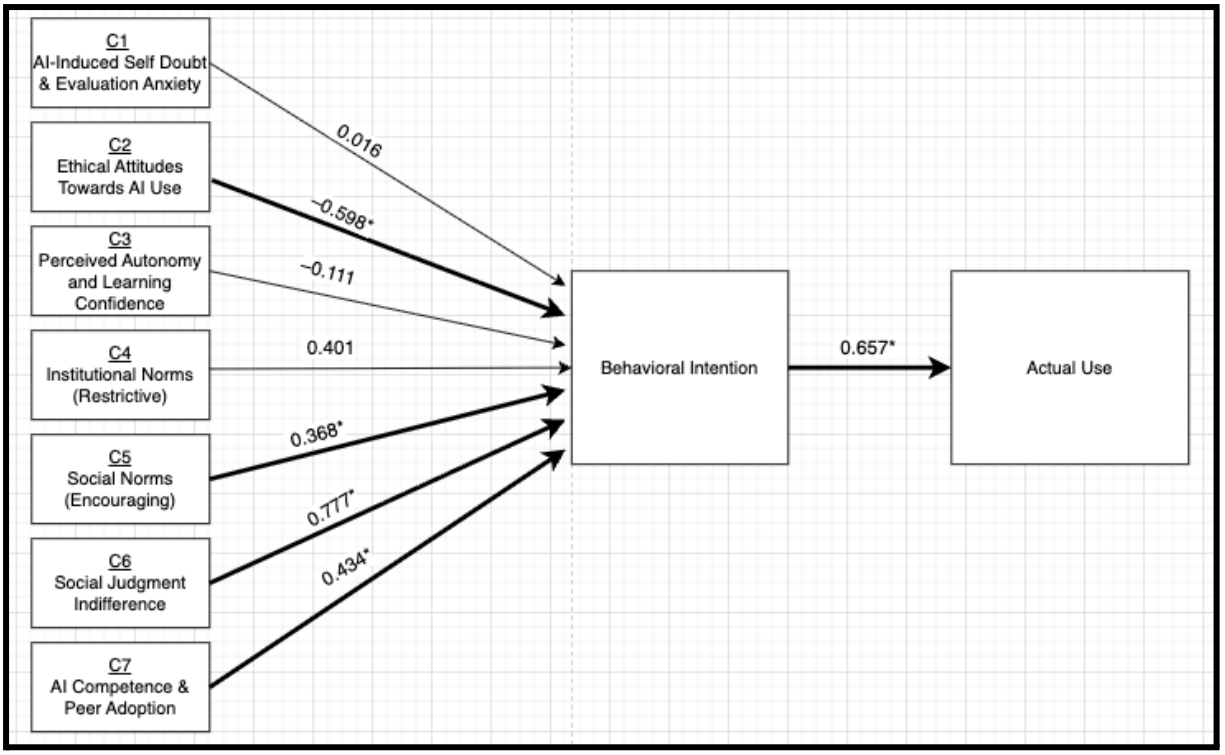


Figure 4. Structural Equation Model Results with standardized path coefficients. Significant relationships are indicated with bold arrows ($p < .05$)

6. Discussion

6.1 Key Findings & Contributions

This study contributes to the existing growing body of research on Generative AI (Gen AI) adoption in education by introducing and empirically validating a novel construct, AI Guilt, as a multidimensional psychological phenomenon that captures students' emotional conflict, ethical concerns, and perceived social expectations surrounding the use of Gen AI in academic settings. While prior research has addressed factors like usefulness, ease of use, or fear of automation, this study introduces a more human centered perspective on how students navigate the evolving landscape of Gen AI in education.

Through Exploratory and Confirmatory Factor Analysis, seven distinct components of AI Guilt were identified (C1-C7) containing items adapted from existing frameworks: Imposter Syndrome, Fear of Negative Evaluation, Attitudes Towards Plagiarism, Subjective Norms, and Perceived Behavioural Control. These components reflect a layered psychological reality, not only whether the students use Gen AI tools but also how they feel about their use, how they believe others perceive it, and how competent or autonomous they feel in managing it.

The study's first contribution is the development of a validated measurement instrument for AI Guilt. This framework broadens the theoretical landscape of Gen AI research in education by offering a scale that future researchers can adopt or adapt in academic studies to assess how emotional and normative forces shape the Gen AI use beyond simple utility based or rational choice assumptions.

Secondly, the results offer a conceptual extension of the Theory of Planned Behaviour (TPB) by demonstrating that guilt based constructs can meaningfully interact with classical TPB predictors like attitudes, norms, and control beliefs. The relationship between AI Guilt and Behavioural Intention was neither linear nor uniformly negative. Certain components of AI Guilt -that for example, refer to concerns about academic misconduct- discourage the intention to use, while others -that for example, refer to perceived pressure from peers or self-efficacy in using the tools- appear to coexist with or even add to these intentions. This shows that AI Guilt does not function as simple passive resistance but as a complex mediator embedded in students' value systems and perceptions.

Thirdly, the findings highlight the diverse and sometimes contradictory roles that different forms of guilt related experience can play. For instance, students experiencing Social Judgment Indifference (C1/C6), which reflects elements of Fear of Negative Evaluation, may still intend to use Gen AI tools when Social Norms (Encouraging) (C5) is strong.

At last, the study confirms that Behavioural Intention remains a significant predictor of actual Gen AI usage among students, in line with what the Theory of Planned Behavior has suggested. Despite the presence of guilt related hesitation, students who express a strong intention to use these tools are indeed more likely to do so in practice.

6.2 Theoretical Implications

The study offers a few important theoretical implications for models of technology adoption, the psychology of academic behaviour, and the evolving conceptualization of AI related emotions and experiences in the context of education.

To begin, the findings challenge the assumption that psychological constructs such as the Imposter Syndrome (ISY), Fear of Negative Evaluation (FNE), Attitudes Towards Plagiarism (ATP), and the Theory of Planned Behaviour (TPB) can be treated as empirically distinct when applied to Gen AI usage. As already mentioned earlier, items from these constructs are cross loaded onto new shared components, and this overlap suggests that students experience discomforts regarding their Gen AI use in ways that do not align smoothly with what science has established as its boundaries. This is a signal to reconsider the structure of psychological dynamics when new technologies disrupt existing academic work.

According to the results, the use of AI Guilt as a straightforward mediator construct is more complicated. Although our initial theory suggested that it was going to act as a link between the TPB items and BI, it did not display a consistent direct influence. Some components had the expected negative influence on BI, while others had positive effects. When evaluating guilt, one should consider its nature and the surrounding circumstances (emotional, ethical, social, financial, geographical, etc.). This observation challenges TPB's assumption of clean and very rational paths from beliefs to behaviour and asks for an expansion to integrate the emotional ambiguity.

Additionally, the limitations of the hypothesis testing were exposed when empirical structures deviate from established theory. Several of our hypotheses assumed that specific latent variables would map cleanly onto individual constructs, but in reality the observed component structure made this alignment impossible. As a result, testing these hypotheses in a traditional structural equation modeling way was messy. Therefore, we understand that validation methods like this may be inappropriate when new constructs have unclear limits. In this sense, the failures we documented earlier as "non-significant" or contradictions do actually have theoretical meaning.

At last, it was emphasized how important it is to view the discomfort that arises from the use of Gen AI tools as a key variable that requires its own attention with theory to back it up rather than viewing it as noise in the background or resistance. The students' choices to use Gen AI cannot be explained simply by terms like ease of use, subjective norms, etc., but it needs to more clearly consider the end-to-end emotional experience as these tools become more and more integrated into academic settings. For something like this, a very thorough documentation needs to take place on a way bigger sample scale.

6.3 Practical Implications

The development and validation of the AI Guilt concept as a tool for understanding the students' experience when engaging with Gen AI tools provides a key implication. Instead of thinking that students either abuse Gen AI or don't use it at all because of clear-cut attitudes or technical limitations, the AI Guilt scale shows how complex their uncertainty is behind their choices. It would be greatly beneficial for institutions to deploy this framework in order to diagnose not just whether the use is taking place but also how conflicted or ethically confused they feel when doing so. More advanced support systems are needed, not just systems that rely either on compliance or surveillance, but instead encourage academic integrity and moral reflection from a place of understanding.

According to the results, guilt does not always prohibit people from using Gen AI. Sometimes it can work towards their purpose or even make it stronger, especially when they are under a lot of social pressure or believe they are good at what they are doing. Programs that try to stop misuse by using guilt based messages and demonizing AI might not be effective or even be counterproductive. Instead, institutions should focus on making clear boundaries around acceptable use and normalising academic discussions about when and how Gen AI tools can be appropriately used, reducing the additional psychological burden of guessing or fear and judgment.

The fact that several psychological concepts came together in the real world to form shared guilt dimensions shows that schools need to stop focusing on isolated issues like plagiarism, contract cheating, AI misuse, etc., and instead create interdisciplinary student support models that understand how all issues are connected. Counseling services, academic advisors, and AI Literacy programs should be able to handle all of these areas. This calls for not just teaching how to use such tools or follow rules but also being able to help students to deal with their internal conflicts and the peer dynamics around Gen AI use.

Finally, the strong predictive power of Behavioural Intention on Actual Use shows how important it is to shape the students' intentions before enforcing policies. If the intention drives action, then educational environments that are transparent, supportive, and consistent in their messaging regarding AI are more likely to foster and inspire responsible usage. Therefore, one way forward is for institutions to prioritize clear, consistent communication about AI norms across all classes, assignments, and examinations. When ambiguity exists, guilt and confusion are likely to flourish.

6.4 Limitations & Future Research Directions

While this study provides a novel contribution to the literature by introducing and validating the AI Guilt construct, several limitations must be acknowledged. Rather than diminishing the study's value, these limitations highlight theoretical and methodological directions for future extension and enhancement of the research. These findings are interpreted based on the empirically derived components (C1-C7), which represent merged dimensions of the original constructs.

Firstly, the structure of the AI Guilt concept was different from what was anticipated initially based on theory. During EFA, items from different frameworks grouped together in unexpected ways. This overlap makes it harder to come up with a clean theoretical interpretation. Feelings of guilt related to GenAI usage may not be smoothly separable into standard, already validated constructs. Future research could look into different modeling approaches such as network analysis (assumes a dynamic, self-reinforcing system) or latent profile analysis (assumes unobserved groups exist), which may better capture how guilt is linked to AI technology adoption in academic settings.

Following this, the structure model was based on the idea that people make decisions in a linear and rational decision path, as assumed by the Theory of Planned Behaviour. However, the findings suggest a link between guilt and behaviour might be more hard to unfold than just a pure mechanism that prohibits people from doing things that are considered not acceptable or bad. Higher levels of guilt were linked to increased Behavioural Intention. Guilt may also be a sign of a greater moral engagement, of increased academic integrity, or of perceived competence rather than simply an avoidance motivation. To better understand this, it might be helpful to discover and integrate more than just rational choice frameworks in future work, like emotional ambivalence models (conflicting positive and negative evaluations towards the same behaviour), identity based theory (Behaviour serves as a mechanism for self-verification), or signaling perspectives (actions are symbolic communication to convey a status).

Moving on, several survey items were removed during scale validation due to low loadings (FNE12, ATP2, ATP4, FNE10). While this was methodologically dictated to preserve the construct validity, it also suggests that certain psychological predictors may not work well in the Gen AI context. As technology and institutions continue to evolve, so do the students' perceptions of academic AI use. In the research to come, the refinement measurement approaches could be revisited to include testing revised item wording, developing Gen AI specific guilt indicators, or validating the construct across different fields and institutional environments and levels.
Next, the study employed an acceptable sample in terms of diversity and overall size. The dataset was split into two subsets, with EFA conducted on the first half and CFA on the other, to ensure

independent validation of the measurement model. However, the total size (N = 158) and, consequently, the reduced size of each subset is relatively modest for complex SEM analysis, which may limit statistical power and the stability of the results. On top of this, the data is cross-sectional and self-reported, which makes it difficult to draw conclusions about cause and effect, particularly given the sensitivity of the topics involved in the survey. In future research, these limitations could be addressed through longitudinal or more explorative and experimental designs. For example, researchers could examine how AI Guilt and Gen AI use behaviours evolve over time, particularly in response to institutional policy updates, before and after AI Literacy programs or changes in the way of work in the assignments and the examinations.

Aside from all these, there are a number of promising areas for future study to help us understand AI Guilt more substantially. Looking into whether AI Guilt is a stable trait or a situational state that changes depending on the setting is a very useful path. Feelings of guilt may fluctuate based on the assignment's importance, the amount of time available, the type of assessment, or the perceived risk of being caught and the amount of flexibility the consequences imply. Separating the state and trait aspects could make it much easier to predict how Gen AI will act on Behaviour and help explain the variability in the students' responses across contexts.

In the same spirit, subsequent studies could look into how AI Guilt changes as a student grows up. It is possible that students at different stages of their academic paths absorb academic norms differently, suggesting the first year students, final year students, postgraduate students, different generations of students like Gen Z vs. Millennials, or students from different disciplinary backgrounds may experience and respond to AI Guilt in various ways. This kind of work could help with clarifying how academic identity formation interacts with moral feelings in shaping Gen AI adoption behaviour.

Another interesting direction is to dive into the relationship between AI Guilt and performance outcomes. While the current study focuses on Behavioural Intention and Actual Use, guilt may also influence performance indirectly. For example, guilt could increase performance anxiety and encourage excessive verification behaviour, or lead to more cautious and reflective use of Gen AI tools. Finding out whether AI Guilt improves or undermines academic success in the long run would make the concept more useful in both theory and practice.

Further research might also take advantage of the institutional "policy shock." As universities continue to update or generate GenAI policies, researchers can look at how students felt and behaved before and after the policies were put in place. These kinds of quasi experimental approaches may contribute insights on how AI Guilt will be affected and how people will act as a result of it.

Adding views from moral psychology perspectives such as moral licensing may offer further explanation for patterns that seem to be contradicting each other. Some students may reduce Gen AI use when experiencing guilt, while others may justify their use through perceived normative behaviour (e.g., "everyone else is using it," "I've learned a shortcut," "I've done the hardest part," "I've never missed a class," "it's just for brainstorming," "English is my second language," "I will master my skills in the future," etc.). Exploring these dynamics may enlighten why guilt does not uniformly reduce Gen AI adoption.

Finally, future research can explore how AI Guilt evolves as students use Gen AI more and more day by day. As AI tools shift from being perceived as external tools towards collaborative partners or even cognitively integrated partners -especially considering the accessibility nowadays- guilt responses may disappear or transform. Longitudinal research assessing how human-AI identity integration develops over time could help us understand how people's minds change when they use Gen AI in the classroom.

References

ACODS UK (2023, February 13). French university prohibits ChatGPT usage by students. Medium. https://medium.com/@Acods/french-university-prohibits-chatgpt-usage-by-students-495ed2fa57bc

Adel, A., Ahsan, A., & Davison, C. (2024). ChatGPT Promises and Challenges in Education: Computational and Ethical Perspectives. Education Sciences, 14(8), 814. https://doi.org/10.3390/educsci14080814

AI Singapore and the United Nations Development Programme collaborate to close the AI literacy divide & transform communities in developing countries. (2025, May 29). UNDP. https://www.undp.org/policy-centre/singapore/press-releases/ai-singapore-and-united-nations-development-programme-collaborate-close-ai-literacy-divide-transform

AI usage Guidelines. (n.d.). Erasmus University. https://www.eur.nl/en/about-university/policy-and-regulations/regulations-and-guidelines/ai-usage-guidelines

AI Use in Assessments: Your role in protecting the integrity of qualifications - JCQ Joint Council for Qualifications. (2025, April 30). JCQ Joint Council for Qualifications. https://www.jcq.org.uk/exams-office/malpractice/artificial-intelligence/

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-t

Arrindell, W. (2003). Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations. Behaviour Research and Therapy, 41(7), 861–862. https://doi.org/10.1016/s0005-7967(02)00184-5

Augusta University. (2024, August). The CWE's approach to GENAI. https://www.augusta.edu/cwe/approachestogenai.php

Baek, C., Tate, T., & Warschauer, M. (2024). "ChatGPT seems too good to be true": College students' use and perceptions of generative AI. Computers and Education Artificial Intelligence, 7, 100294. https://doi.org/10.1016/j.caeai.2024.100294

Bannister, P., Peñalver, E. A., & Urbieta, A. S. (2024). International Students and generative Artificial Intelligence. Journal of International Students, 14(3), 149–170. https://doi.org/10.32674/jis.v14i3.6277 // https://files.eric.ed.gov/fulltext/EJ1423369.pdf

Bašić, Ž., Banovac, A., Kružić, I., & Jerković, I. (2023). ChatGPT-3.5 as writing assistance in students' essays. Humanities and Social Sciences Communications, 10(1). https://doi.org/10.1057/s41599-023-02269-7

Baume, D. (2013). Originality and education. ojs.aishe.org. https://doi.org/10.62707/aishej.v5i2.128

Baumeister, R. F., Stillwell, A. M., & Heatherton, T. F. (1994). Guilt: An interpersonal approach. Psychological Bulletin, 115(2), 243–267. https://doi.org/10.1037/0033-2909.115.2.243 // https://www.researchgate.net/publication/15034528_Guilt_An_Interpersonal_Approach

Bewersdorff, A., Hornberger, M., Nerdel, C., & Schiff, D. S. (2024). AI advocates and cautious critics: How AI attitudes, AI interest, use of AI, and AI literacy build university students' AI self-efficacy. Computers and Education Artificial Intelligence, 8, 100340. https://doi.org/10.1016/j.caeai.2024.100340

Bin-Nashwan, S. A., Sadallah, M., & Bouteraa, M. (2023). Use of ChatGPT in academia: Academic integrity hangs in the balance. Technology in Society, 75, 102370. https://doi.org/10.1016/j.techsoc.2023.102370

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., . . . Amodei, D. (2020). Language Models are Few-Shot Learners. *arXiv (Cornell University)*, *33*, 1877–1901. https://doi.org/10.48550/arxiv.2005.14165

Busby, E. (2023, March 30). Pupils should do some coursework 'in front of teachers' amid AI cheating fears. The Independent. https://www.independent.co.uk/news/uk/politics/joint-council-for-qualifications-chatgpt-schools-mps-google-b2310108.html

Capitalist, V. (2025, March 20). ChatGPT continues to reign supreme 🤖. Voronoi. https://www.voronoiapp.com/technology/ChatGPT-Continues-To-Reign-Supreme--4422

Cassidy, C. (2024, November 25). Voice from the past: how one university is countering AI with ancient examination techniques. The Guardian. https://www.theguardian.com/australia-news/2024/nov/25/back-to-the-futurum-how-one-university-is-countering-ai-with-ancient-examination-techniques

Chakraverty, D. (2020. March 6). PhD Student Experiences with the Impostor Phenomenon in STEM. https://www.informingscience.org/Publications/4513 // https://ijds.org/Volume15/IJDSv15p159-179Chakraverty6025.pdf

Chan, C. (2024). Holistic competencies and AI in education: A synergistic pathway. Australasian Journal of Educational Technology, 40(5), 1–12. https://doi.org/10.14742/ajet.10191

Chan, C. K. Y. (2024). Exploring the factors of "AI guilt" among students -- Are you guilty of using AI in your homework? arXiv (Cornell University). https://doi.org/10.48550/arxiv.2407.10777

Chan, C. K. Y. (2024). Students' perceptions of 'AI-giarism': investigating changes in understandings of academic misconduct. *Education and Information Technologies*, *30*(6), 8087–8108. https://doi.org/10.1007/s10639-024-13151-7

Chan, C. K. Y. (2025). Understanding AI guilt: the development, pilot-testing, and validation of an instrument for students. Education and Information Technologies, 30(15), 21727–21746. https://doi.org/10.1007/s10639-025-13629-y

Chapter 8 Attention and Self-Attention for NLP | Modern Approaches in Natural Language Processing. (2020. September 8). https://slds-lmu.github.io/seminar_nlp_ss20/attention-and-self-attention-for-nlp.html

Chazan, D. (2025, June 18). French students banned from using computers during lectures. The Times. https://www.thetimes.com/world/europe/article/french-students-banned-from-using-computers-during-lectures-ncs8j6z8q // http://archive.ph/mU1mT#selection-1511.0-1514.0

Chow, A. R. (2025, June 23). ChatGPT may be eroding critical thinking skills, according to a new MIT study. TIME. https://time.com/7295195/ai-chatgpt-google-learning-school/

Chu, T., & Chen, Y. (2015). With Good We Become Good: Understanding e-learning adoption by theory of planned behavior and group influences. Computers & Education, 92–93, 37–52. https://doi.org/10.1016/j.compedu.2015.09.013

Churchill, G. A., & Jr. (1979). A paradigm for developing better measures of marketing constructs. *Journal of Marketing Research*, *16*(1), 64–73. https://doi.org/10.2307/3150876https://www.jstor.org/stable/3150876

Clance, P. R., & Imes, S. A. (1978). The imposter phenomenon in high achieving women: Dynamics and therapeutic intervention. Psychotherapy, 15(3), 241–247. https://doi.org/10.1037/h0086006

Cokley, K. O., Bernard, D. L., Stone-Sabali, S., & Awad, G. H. (2024). Impostor phenomenon in Racially/Ethnically Minoritized Groups: Current knowledge and future directions. Annual Review of Clinical Psychology, 20(1), 407–430. https://doi.org/10.1146/annurev-clinpsy-081122-015724

Cooper, G., Barkatsas, T., & Strathdee, R. (2016). The Theory of Planned Behaviour (TPB) in Educational Research using Structural Equation Modelling (SEM). In SensePublishers eBooks (pp. 139–162). https://doi.org/10.1007/978-94-6300-761-0_9

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2023). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. Innovations in Education and Teaching International, 61(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148

Country Comparison Bar Charts - Geert Hofstede. (n.d.). Geert Hofstede. https://geerthofstede.com/country-comparison-bar-charts/

Dangol, A., Wolfe, R., Yoo, D., Thiruvillakkat, A., Chickadel, B., & Kientz, J. A. (2025). “If anybody finds out you are in BIG TROUBLE”: Understanding Children’s Hopes, Fears, and Evaluations of Generative AI. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2505.16089

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Davis, S. (2023, June 19). *AI Shame: Should you feel guilty for using AI in your job?* Botcratic - AI News. https://www.botcratic.com/ai-shame-should-you-feel-guilty-for-using-ai-in-your-job/

Digital Education Council. (2024, August 7). What Students Want: Key Results from DEC Global AI Student Survey 2024. https://www.digitaleducationcouncil.com/post/what-students-want-key-results-from-dec-global-ai-student-survey-2024

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2014). Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology General, 144(1), 114–126. https://doi.org/10.1037/xge0000033

Dignum, V. (2021). The role and challenges of education for responsible AI. London Review of Education, 19(1). https://doi.org/10.14324/lre.19.1.01

Draxler, F., Werner, A., Lehmann, F., Hoppe, M., Schmidt, A., Buschek, D., & Welsch, R. (2023). The AI ghostwriter effect: when users do not perceive ownership of AI-Generated text but Self-Declare as authors. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2303.03283

Duarte, F. (2025, December 14). Number of ChatGPT users (January 2026). Exploding Topics. https://explodingtopics.com/blog/chatgpt-users

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., . . . Wright, R. (2023). Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. International Journal of Information Management, 71, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Edubirdie (2025, December 3). *The AI generation: How Generation Z is taking ChatGPT into the workplace*. Edubirdie Blog. https://edubirdie.com/blog/generation-z-ai-workplace-insights

Edelman. (2025). The AI Trust Imperative: Navigating the Future with Confidence. https://www.edelman.com/trust/2025/trust-barometer/report-tech-sector

Ehrich, J., Howard, S., Tognolini, J., & Bokosmaty, S. (2015). Measuring attitudes toward plagiarism: issues and psychometric solutions. Journal of Applied Research in Higher Education, 7(2), 243–257. https://doi.org/10.1108/jarhe-02-2014-0013

Ellis, L., & Images, R. N. (2024, April 3). Business schools are going all in on AI. The Wall Street Journal. https://www.wsj.com/tech/ai/generative-ai-mba-business-school-13199631 //https://archive.ph/hk1fo

Erdawati, E., Suryoputro, G., & Hikmat, A. (2025). Impact of the integration of generative AI-Automatic Corrective feedback on academic writing skills. International Journal of Learning Teaching and Educational Research, 24(5), 214–230. https://doi.org/10.26803/ijlter.24.5.11

European Commission. (2024). AI Act\Shaping Europe's Digital Future. https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai

Farooq, R., & Sultana, A. (2021). Measuring students' attitudes toward plagiarism. Ethics & Behavior, 32(3), 210–224. https://doi.org/10.1080/10508422.2020.1860766

Fearn, N. (2024, June 6). Educators warn AI must be a teaching — not a cheating — aid. Financial Times. https://www.ft.com/content/26ff910a-d19e-444b-9e4c-f06e6d546db3

Flaherty, C. (2025, April 21). Half of colleges don't grant students access to Gen AI tools. Inside Higher Ed | Higher Education News, Events and Jobs.

https://www.insidehighered.com/news/tech-innovation/artificial-intelligence/2025/04/21/half-colleges-dont-grant-students-access

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People—An Ethical Framework for a Good AI Society: Opportunities, risks, principles, and recommendations. Minds and Machines, 28(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5

Fowler, G. A. (2023, August 17). What to do when you're accused of AI cheating. The Washington Post. https://www.washingtonpost.com/technology/2023/08/14/prove-false-positive-ai-detection-turnitin-gptzero/

Fritz, J. (2025). Understanding authorship in Artificial Intelligence-assisted works. Journal of Intellectual Property Law & Practice, 20(5), 354–364. https://doi.org/10.1093/jiplp/jpae119

Fütterer, T., Fischer, C., Alekseeva, A., Chen, X., Tate, T., Warschauer, M., & Gerjets, P. (2023). ChatGPT in education: global reactions to AI innovations. Scientific Reports, 13(1), 15310. https://doi.org/10.1038/s41598-023-42227-6

Gannon, K. (2024, June 27). Should you add an AI policy to your syllabus? The Chronicle of Higher Education. https://www.chronicle.com/article/should-you-add-an-ai-policy-to-your-syllabus // https://archive.ph/rIK7Y#selection-2505.9-2508.0

Generative AI guidelines. (n.d.). Utrecht University. https://students.uu.nl/en/gsls/rules-and-guidelines/generative-ai-guidelines

Gillespie, N., Lockey, S., Curtis, C., Pool, J., & Akbari, A. (2023). Trust in Artificial Intelligence: A global study. https://doi.org/10.14264/00d3c94 // https://assets.kpmg.com/content/dam/kpmgsites/au/pdf/2023/trust-in-ai-global-insights-2023.pdf

Giray, L. (2024). AI Shaming: The Silent Stigma among Academic Writers and Researchers. *Annals of Biomedical Engineering*, *52*(9), 2319–2324. https://doi.org/10.1007/s10439-024-03582-1

Goode, L., Calore, M., & Drummond, K. (2025, May 23). Let's talk about ChatGPT and cheating in the classroom. WIRED. https://www.wired.com/story/uncanny-valley-podcast-chatgpt-cheating-in-the-classroom/ // https://archive.ph/WvxJT#selection-493.0-496.0

Government AI Readiness Index 2025 - Oxford Insights. (2025, January 7). Oxford Insights. https://oxfordinsights.com/ai-readiness/government-ai-readiness-index-2025/

Gregg, I. (2024, August 13). The Future of Work: Embracing AI's job creation potential. Forbes. https://www.forbes.com/councils/forbestechcouncil/2024/03/12/the-future-of-work-embracing-ais-job-creation-potential/

Gruenhagen, J. H., Sinclair, P. M., Carroll, J., Baker, P. R., Wilson, A., & Demant, D. (2024). The rapid rise of generative AI and its implications for academic integrity: Students' perceptions and use of chatbots for assistance with assessments. Computers and Education Artificial Intelligence, 7, 100273. https://doi.org/10.1016/j.caeai.2024.100273

Hamm, J. (2024, May). Imposter Syndrome: Navigating as a First-Generation College student. Digital Commons @ CSUMB. https://digitalcommons.csumb.edu/caps_thes_all/1765/

Haque, M. A., & Li, S. (2023). The potential use of ChatGPT for debugging and bug fixing. EAI Endorsed Transactions on AI and Robotics, 2(1), e4. https://doi.org/10.4108/airo.v2i1.3276

Heider, F. (1958). The psychology of interpersonal relations. https://doi.org/10.1037/10628-000

Hinkin, T. R. (1998). A brief tutorial on the development of measures for use in survey questionnaires. *Organizational Research Methods*, *1*(1), 104–121. https://doi.org/10.1177/109442819800100106

Ho, C. C. (2023). ChatGPT as a tool for developing paraphrasing skills among ESL learners. ResearchGate. https://www.researchgate.net/publication/375799764_ChatGPT_as_a_Tool_for_Developing_Paraphrasing_Skills_Among_ESL_Learners

Hofstede, G. (2011, December). Dimensionalizing Cultures: The Hofstede Model in context. ScholarWorks@GVSU. https://scholarworks.gvsu.edu/orpc/vol2/iss1/8/

Huang, D., Hash, N., Cummings, J. J., & Prena, K. (2025). Academic cheating with generative AI: Exploring a moral extension of the theory of planned behavior. Computers and Education Artificial Intelligence, 8, 100424. https://doi.org/10.1016/j.caeai.2025.100424

Husain, F. M., Al-Shaibani, G. K. S., & Mahfoodh, O. H. A. (2017). Perceptions of and Attitudes toward Plagiarism and Factors Contributing to Plagiarism: a Review of Studies. Journal of Academic Ethics, 15(2), 167–195. https://doi.org/10.1007/s10805-017-9274-1

IBM. What are AI hallucinations? Ibm Blog. https://www.ibm.com/think/topics/ai-hallucinations

Iraola-Real, I., Vasquez, C., Diaz-Leon, I., & Iraola-Arroyo, A. (2023). Self-Efficacy and Digital Anxiety and their Influence on Virtual Educational Performance. International Journal of Emerging Technologies in Learning (iJET), 18(09), 165–179. https://doi.org/10.3991/ijet.v18i09.36183

Jo, H. (2024). From concerns to benefits: a comprehensive study of ChatGPT usage in education. International Journal of Educational Technology in Higher Education, 21(1). https://doi.org/10.1186/s41239-024-00471-4

Joey Chee. (14) Navigating Guilt: Feeling Guilty about Using AI for Work? | LinkedIn. (2023, June 20). https://www.linkedin.com/pulse/navigating-guilt-feeling-guilty-using-ai-work-joey-chee-1c/

Jonathan S. Jones. (2023, September 7). Students critique a ChatGPT essay. https://www.historians.org/perspectives-article/students-critique-a-chatgpt-essay-a-classroom-experiment-september-2023/

Julie Jargon (2025, May 31). Students are humanizing their Writing—By putting it through AI. tovima.com. https://www.tovima.com/wsj/students-are-humanizing-their-writing-by-putting-it-through-ai/

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A.,

Seidel, T., . . . Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Khlaif, Z. N., Alkouk, W. A., Salama, N., & Eideh, B. A. (2025). Redesigning Assessments for AI-Enhanced Learning: A framework for educators in the Generative AI era. Education Sciences, 15(2), 174. https://doi.org/10.3390/educsci15020174

Kim, J., Klopfer, M., Grohs, J. R., Eldardiry, H., Weichert, J., Cox, L. A., & Pike, D. (2025). Examining faculty and student perceptions of generative AI in university courses. Innovative Higher Education, 50(4), 1281–1313. https://doi.org/10.1007/s10755-024-09774-w

Langreo, L. (2025, January 31). Schools' AI policies are still not clear to teachers and students. Education Week. https://www.edweek.org/technology/schools-ai-policies-are-still-not-clear-to-teachers-and-students/2025/01

Larcker, C. F. a. D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312https://www.jstor.org/stable/3151312

Leary, M. R. (1983). A brief version of the fear of negative evaluation scale. Personality and Social Psychology Bulletin, 9(3), 371–375. https://doi.org/10.1177/0146167283093007

Leary, M. R., Patton, K. M., Orlando, A. E., & Funk, W. W. (2000). The impostor phenomenon: Self‐Perceptions, reflected appraisals, and interpersonal strategies. Journal of Personality, 68(4), 725–756. https://doi.org/10.1111/1467-6494.00114

Liang, W., Yuksekgonul, M., Mao, Y., Wu, E., & Zou, J. (2023). GPT detectors are biased against non-native English writers. Patterns, 4(7), 100779. https://doi.org/10.1016/j.patter.2023.100779

Lyu, W., Zhang, S., Chung, T., Sun, Y., & Zhang, Y. (2025). Understanding the practices, perceptions, and (dis)trust of generative AI among instructors: A mixed-methods study in the U.S. higher education. Computers and Education Artificial Intelligence, 8, 100383. https://doi.org/10.1016/j.caeai.2025.100383

McDonald, N., Johri, A., Ali, A., & Collier, A. H. (2025). Generative artificial intelligence in higher education: Evidence from an analysis of institutional policies and guidelines. Computers in Human Behavior Artificial Humans, 3, 100121. https://doi.org/10.1016/j.chbah.2025.100121

Mekheimer, M. (2025). Technological self-efficacy, motivation, and contextual factors in advanced EFL e-learning: a mixed-methods study of strategy use and satisfaction. Humanities and Social Sciences Communications, 12(1). https://doi.org/10.1057/s41599-025-04947-0

Miller, D. T., & Ross, M. (1975). Self-serving biases in the attribution of causality: Fact or fiction? Psychological Bulletin, 82(2), 213–225. https://doi.org/10.1037/h0076486 // https://web.mit.edu/curhan/www/docs/Articles/biases/82_Psychological_Bulletin_213_%28Miller%29.pdf

Ministerie van Algemene Zaken. (2024, January 24). Government-wide vision on generative AI of the Netherlands. Parliamentary Document | Government.nl.

https://www.government.nl/documents/parliamentary-documents/2024/01/17/government-wide-vision-on-generative-ai-of-the-netherlands

MIT. (2025, February 19). Guidance for use of Generative AI tools. https://ist.mit.edu/ai-guidance

Morin, V. (2025, November 5). Artificial intelligence: How ChatGPT is transforming cheating in schools. Le Monde.fr. https://www.lemonde.fr/en/france/article/2025/02/11/artificial-intelligence-how-chatgpt-is-transforming-cheating-in-schools_6738013_7.html

Mowreader, A. (2024, June 28). One-third of college instructors are using genAI—here's how. Inside Higher Ed | Higher Education News, Events and Jobs. https://www.insidehighered.com/news/student-success/academic-life/2024/06/28/one-third-college-instructors-are-using-genai-heres

Mowreader, A. (2024, September 16). College students uncertain about AI policies in classrooms. Inside Higher Ed | Higher Education News, Events and Jobs. https://www.insidehighered.com/news/student-success/academic-life/2024/09/16/college-students-uncertain-about-ai-policies

Navigating Guilt: Feeling Guilty about Using AI for Work? | LinkedIn. (2023, June 20). https://www.linkedin.com/pulse/navigating-guilt-feeling-guilty-using-ai-work-joey-chee-1c/

Nekrasova, D. (2024, January 10). "The more you know, the less you fear.": A quantitative study on the effects of AI literacy, AI self-efficacy and perception of AI uncanniness on AI anxiety amongst adults. https://thesis.eur.nl/pub/75057/

New York Institute of Technology. (2023, August 21). To permit or to prohibit? Sample Syllabus Statements for Generative AI. https://blogs.nyit.edu/cfe-weekly-teaching-notes/to_permit_or_to_prohibit_sample_syllabus_statements_for_generative_ai

Nguyen-Phuong-Mai, (2015). HOFSTEDE'S FIVE VALUE DIMENSIONS OF CULTURE Amsterdam University of Applied Sciences. https://www.amsterdamuas.com/binaries/content/assets/subsites/international-business-school-ibs/chapter-3-hofstede-values-on-website.pdf

Nosta, J. (2025, March 13). The uneasy feeling of outsourcing your own intelligence. Psychology Today. https://www.psychologytoday.com/us/blog/the-digital-self/202503/ai-and-the-new-impostor-syndrome

OpenAI, Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F. L., Almeida, D., Altenschmidt, J., Altman, S., Anadkat, S., Avila, R., Babuschkin, I., Balaji, S., Balcom, V., Baltescu, P., Bao, H., Bavarian, M., Belgum, J., . . . Zoph, B. (2023, March 15). *GPT-4 Technical Report*. arXiv.org. https://arxiv.org/abs/2303.08774

Opesemowo, O. a. G. (2025). Teachers' attitude towards the use of CHATGPT for educational assessment. International Journal of Humanities Education and Social Sciences (IJHESS), 4(4). https://doi.org/10.55227/ijhess.v4i4.1352

Ozkaya, M. (2024, December 4). LLM models: OpenAI ChatGPT, Meta LLaMA, Anthropic Claude, Google Gemini, Mistral AI, and xAI grok. Medium https://mehmetozkaya.medium.com/llm-models-openai-chatgpt-meta-llama-anthropic-claude-google-gemini-mistral-ai-and-xai-grok-bd35779704c2

Policy Framework Generative Artificial Intelligence. (2024, December). Policy Framework Generative Artificial Intelligence. Maastricht University https://www.maastrichtuniversity.nl/file/policy-framework-generative-artificial-intelligence-12-12-2024pdf

Polyportis, A. (2024). A longitudinal study on artificial intelligence adoption: understanding the drivers of ChatGPT usage behavior change in higher education. Frontiers in Artificial Intelligence, 6, 1324398. https://doi.org/10.3389/frai.2023.1324398

Price, P. C., Holcomb, B., & Payne, M. B. (2024). Gender differences in impostor phenomenon: A meta-analytic review. Current Research in Behavioral Sciences, 7, 100155. https://doi.org/10.1016/j.crbeha.2024.100155

Qu, Y., & Wang, J. (2025). The impact of AI guilt on students' use of ChaTGPT for academic tasks: Examining disciplinary differences. Journal of Academic Ethics, 23(4), 2087–2110. https://doi.org/10.1007/s10805-025-09643-x

Reuters. (2023, January 27). Top French university bans use of ChatGPT to prevent plagiarism. Reuters. https://www.reuters.com/technology/top-french-university-bans-use-chatgpt-prevent-plagiarism-2023-01-27/

Rosenstein, A., Raghu, A., & Porter, L. (2020). Identifying the Prevalence of the Impostor Phenomenon Among Computer Science Students. Proceedings of the 51st ACM Technical Symposium on Computer Science Education. https://doi.org/10.1145/3328778.3366815

Rubio-Licht, N. (2025, May 19). AI may never completely conquer hallucination, bias. The Daily Upside. https://www.thedailyupside.com/technology/artificial-intelligence/ai-may-never-completely-conquer-hallucination-bias/

Ruediger, D., Blankstein, M., & Love, S. J. (2024, June 20). Generative AI and Postsecondary Instructional Practices: Findings from a National Survey of Instructors. https://doi.org/10.18665/sr.320892

Ryan, H., Abramov, D., Acker, S., & Elkins, S. (2025). Can AI be a Co-Author?: How Generative AI challenges the boundaries of authorship in a general education writing class. https://www.semanticscholar.org/paper/Can-AI-Be-a-Co-Author%3A-How-Generative-AI-Challenges-Ryan-Abramov/ad884155aec2e80588fad1de3544dd62c7572879

Samuel, S. (2025, June 23). My students think it's fine to cheat with AI. Maybe they're onto something. Vox. https://www.vox.com/advice/413189/ai-cheating-college-humanities-education-chatgpt

Scoble-Williams, N., Sinti, D., Vert, G., & Cantrell, S. (2024, April 9). Generative AI and the Future of Work | Deloitte Global. Deloitte. https://www.deloitte.com/global/en/services/consulting/research/generative-ai-and-the-future-of-work.html

Seran, C. E., Tan, M. J. T., Karim, H. A., & AlDahoul, N. (2025). A Conceptual Exploration of Generative AI-Induced Cognitive Dissonance and its Emergence in University-Level Academic Writing. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2502.05698

Shaping the Future of Learning: The role of AI in Education 4.0. (2025, August 25). World Economic Forum. https://www.weforum.org/publications/shaping-the-future-of-learning-the-role-of-ai-in-education-4-0/

Singh, K. (2024, October 21). Transformer architecture. Medium. https://medium.com/@kamalmeet/transformer-architecture-db80b07735a9

Singh, K. (2025, January 27). Understanding Self Attention https://medium.com/@kamalmeet/understanding-self-attention-f605491d152d

Singla, A., Sukharevsky, A., Yee, L. A., & Chui, M. (2025, November 5). The state of AI in 2025: Agents, innovation, and transformation. McKinsey & Company. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai

Stahl, B. C., & Eke, D. (2023). The ethics of ChatGPT – Exploring the ethical issues of an emerging technology. International Journal of Information Management, 74, 102700. https://doi.org/10.1016/j.ijinfomgt.2023.102700

Stone, B. W. (2024). Generative AI in higher Education: uncertain students, ambiguous use cases, and mercenary perspectives. Teaching of Psychology, 52(3), 347–356. https://doi.org/10.1177/00986283241305398

Sullivan, M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. Journal of Applied Learning & Teaching, 6(1). https://doi.org/10.37074/jalt.2023.6.1.17

Tica, L., & Krsmanović, I. (2024). Overcoming the Writer's Block? Exploring students' motivation and perspectives on using ChatGPT as a writing assistance tool in ESP. ELOPE English Language Overseas Perspectives and Enquiries, 21(1), 129–149. https://doi.org/10.4312/elope.21.1.129-149

UNESCO. (2023, June 1). UNESCO survey: Less than 10% of schools and universities have formal guidance on AI. https://www.unesco.org/en/articles/unesco-survey-less-10-schools-and-universities-have-formal-guidance-ai

University of Ofxord. (n.d.). GENAI. https://www.ox.ac.uk/students/life/it/gen-ai

Uzun, A. M., & Kilis, S. (2019). Investigating antecedents of plagiarism using extended theory of planned behavior. Computers & Education, 144, 103700. https://doi.org/10.1016/j.compedu.2019.103700

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017, June 12). *Attention is all you need*. arXiv.org. https://arxiv.org/abs/1706.03762

Watson, D., & Friend, R. (1969). Measurement of social-evaluative anxiety. Journal of Consulting and Clinical Psychology, 33(4), 448–457. https://doi.org/10.1037/h0027806

Weale, S. (2025, February 26). UK universities warned to 'stress-test' assessments as 92% of students use AI. The Guardian. https://www.theguardian.com/education/2025/feb/26/uk-universities-warned-to-stress-test-assessments-as-92-of-students-use-ai

Weeks, J. W., Heimberg, R. G., Fresco, D. M., Hart, T. A., Turk, C. L., Schneier, F. R., & Liebowitz, M. R. (2005). Empirical validation and psychometric evaluation of the brief fear of negative evaluation scale in patients with social anxiety disorder. Psychological Assessment, 17(2), 179–190. https://doi.org/10.1037/1040-3590.17.2.179

Whetsel, K. (2023, July 4). Imposter Syndrome in Higher Education Stems from Self-Doubt and Perfectionism in High School. ScholarWorks@BGSU. https://scholarworks.bgsu.edu/honorsprojects/862/

With Generative AI we can reimagine education — and the sky is the limit. (2025, June 3). World Economic Forum. https://www.weforum.org/stories/2024/02/with-generative-ai-we-can-reimagine-education-and-the-sky-is-the-limi/

Woo, D. J., Wang, D., Yung, T., & Guo, K. (2025). Effects of a prompt engineering intervention on undergraduate students' AI self‐efficacy, AI knowledge and prompt engineering ability: A mixed methods study. British Educational Research Journal. https://doi.org/10.1002/berj.70087

Woolcock, N. (2025, April 24). Gen Z students won't use ChatGPT — but not because it's cheating. The Times. https://www.thetimes.com/uk/education/article/gen-z-students-wont-use-chatgpt-but-not-because-its-cheating-v8rffjlc0 // https://archive.ph/SoqUu#selection-1511.0-1514.0

Xiao, P., Chen, Y., & Bao, W. (2023). Waiting, Banning, and Embracing: An Empirical Analysis of Adapting Policies for Generative AI in Higher Education. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2305.18617

Yu, M., Liu, L., Wu, J., Chung, T. T., Zhang, S., Li, J., Yeung, D., & Zhou, J. (2025). The stochastic parrot on LLM's shoulder: A summative assessment of physical concept understanding. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2502.08946(Chan, 2024)

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: a systematic review. Smart Learning Environments, 11(1). https://doi.org/10.1186/s40561-024-00316-7

Ziegelmayer, J., & James, T. (n.d.). *The impact of threats to professional identity on guilt in the use of artificial intelligence (AI) tools*. AIS Electronic Library (AISeL). https://aisel.aisnet.org/treos_ecis2024/69/

Appendix A: AI Guilt

Component 1 - AI-Induced Self Doubt & Evaluation Anxiety

ISY4: In some academic settings I feel like an imposter when I use ChatGPT or similar GenAI tools.

ISY5: Sometimes I worry that using ChatGPT or similar GenAI tools reveals how much knowledge or how many skills I truly lack.

ISY2: I feel like an imposter when I use ChatGPT or similar GenAI tools for my assignments.

ISY3: I am afraid that my teachers or peers may find out that I rely on ChatGPT or similar GenAI tools more than they expect.

ISY1: I worry that using ChatGPT or similar GenAI tools will make others question my actual academic abilities.

ISY7: In some situations I feel like I am not demonstrating my true academic skills due to my use of ChatGPT or similar GenAI tools.

FNE3: I fear that using ChatGPT or similar GenAI tools will negatively affect how others perceive my academic competence.

FNE9: I am usually concerned about how using ChatGPT or similar GenAI tools affects other people's perception of my intelligence, knowledge, or effort.

FNE5: I am afraid other people will not approve of my use of ChatGPT or similar GenAI tools for academic work and learnings.

FNE11: I sometimes overthink how others perceive my use of ChatGPT or similar GenAI tools.

FNE1: I worry what others will think of me if they find out I use ChatGPT or similar GenAI tools for academic work even when I know it doesnt make a difference.

FNE8: When discussing my academic work, I worry about whether others suspect I used ChatGPT or similar GenAI tools.

ISY6: In some situations I feel like a "great pretender" when i submit work that was fully or partly made by ChatGPT or similar GenAI tools.

FNE6: I am afraid that my professors or classmates will judge me negatively for relying on ChatGPT or similar GenAI tools.

Component 2 - Ethical Attitudes Towards AI Use

ATP1: The use of ChatGPT or similar GenAI tools - generated content should be disclosed.

ATP3: Using ChatGPT or similar GenAI tools - generated content without mentioning it is unethical.

Component 3 - Perceived Autonomy & Learning Confidence

PBC4: Even if I struggle at first, I believe I can learn to use ChatGPT or similar GenAI tools effectively.

PBC2: Whether or not I use ChatGPT or similar GenAI tools is entirely my decision.

Component 4 - Institutional Norms (Restrictive)

SNO5: If my University restricted ChatGPT usage, it would negatively impact my decision to use ChatGPT or similar GenAI tools.

SNO3: If my professors discouraged its use, it would negatively impact my decision to use ChatGPT or similar GenAI tools.

Component 5 - Social Norms (Encouraging)

SNO1: Most people who are important to me think that I should use ChatGPT or similar GenAI tools for my studies.

SNO2: My professors encourage the use of ChatGPT or similar GenAI tools for academic purposes.

Component 6 - Social Judgment Indifference

FNE7: Other people's opinions about my use of ChatGPT or similar GenAI tools do not bother me.

FNE2: I am unconcerned even if my teachers or peers disapprove of my use of ChatGPT or similar GenAI tools.

FNE4: I rarely worry about how using ChatGPT or similar GenAI tools affects other people's impressions of my academic skills.

Component 7 - AI Competence & Peer Adoption

PBC3: I have access to resources that help me use ChatGPT or similar GenAI tools effectively (e.g., internet, documentation, tutorials).

SNO4: My friends/classmates use ChatGPT or similar GenAI tools for their academic tasks.

PBC1: I am confident in my ability to use ChatGPT or similar GenAI tools effectively for academic tasks.

Appendix B: Questionnaire Pre-Refinement Version

To show how the items were refined, the complete list of questionnaire items is provided in Appendix B. The instrument was made shorter by removing the items marked with a strikethrough after the Exploratory Factor Analysis (EFA). The results are in Appendix A.

Demographics + Actual Use	DEM1	Age
	DEM2	Gender
	DEM3	Level of Study
	DEM4	Area of Study
	DEM5	Level of Experience using GenAI
	DEM6	Context of Use of GenAI tools
	AUS1	Actual Use in the Last Month
Imposter Syndrome	ISY1	I worry that using ChatGPT or similar GenAI tools will make others question my actual academic abilities
	ISY2	I feel like an imposter when I use ChatGPT or similar GenAI tools for my assignments
	ISY3	I am afraid that my teachers or peers may find out that I rely on ChatGPT or similar GenAI tools more that they expect
	ISY4	In some academic settings I feel like an imposter when I use ChatGPT or similar GenAI tools
	ISY5	Sometimes I worry that using ChatGPT or similar GenAI tools reveals how much knowledge or how many skills I trully lack
	ISY6	In some situations I feel like a "great pretender" when i submit work that was fully or partly made by ChatGPT or similar GenAI tools
	ISY7	In some situations I feel like I am not demonstrating my true academic skills due to my use of ChatGPT or similar GenAI tools
Fear of Negative Evaluation	FNE1	I worry what others will think of me if they find out I use ChatGPT or similar GenAI tools for academic work even when I know it doesnt make a difference
	FNE2	I am unconcerned even if my teachers or peers disapprove of my use of ChatGPT or similar GenAI tools
	FNE3	I fear that using ChatGPT or similar GenAI tools will negatively affect how others perceive my academic competence
	FNE4	I rarely worry about how using ChatGPT or similar GenAI tools affects other people's impressions of my academic skills
	FNE5	I am afraid other people will not approve of my use of ChatGPT or similar GenAI tools for academic work and learnings
	FNE6	I am afraid that my professors or classmates will judge me negatively for relying on ChatGPT or similar GenAI tools
	FNE7	Other people's opinions about my use of ChatGPT or similar GenAI tools do not bother me
	FNE8	When discussing my academic work, I worry about whether others suspect I used ChatGPT or similar GenAI tools
	FNE9	I am usually concerned about how using ChatGPT or similar GenAI tools affects other people's perception of my intelligence, knowledge, or effort
	~~FNE10~~	~~If I know someone is criticising me for using ChatGPT or similar GenAI tools it has little effect on me~~
	FNE11	I sometimes overthink how others perceive my use of ChatGPT or similar GenAI tools
	~~FNE12~~	~~I often worry that using ChatGPT or similar GenAI tools will make me say or submit wrong things~~
Attitude towards Plagiarism	ATP1	The use of ChatGPT or similar GenAI tools - generated content should be disclosed
	~~ATP2~~	~~In times of ethical uncertainty, it is important to discuss the responsible use of ChatGPT or similar GenAI tools~~
	ATP3	Using ChatGPT or similar GenAI tools - generated content without mentioning it is as unethical
	~~ATP4~~	~~Overreliance on ChatGPT or similar GenAI tools weakens critical thinking and originality~~
Subjective Norms	SNO1	Most people who are important to me think that I should use ChatGPT or similar GenAI tools for my studies
	SNO2	My professors encourage the use of ChatGPT or similar GenAI tools for academic purposes
	SNO3	If my professors discouraged its use, it would negatively impact my decision to use ChatGPT or similar GenAI tools
	SNO4	My friends/classmates use ChatGPT or similar GenAI tools for their academic tasks
	SNO5	If my University restricted ChatGPT usage, it would negatively impact my decision to use ChatGPT or similar GenAI tools
Perceived Behavioral Control	PBC1	I am confident in my ability to use ChatGPT or similar GenAI tools effectively for academic tasks
	PBC2	Whether or not I use ChatGPT or similar GenAI tools is entirely my decision
	PBC3	I have access to resources that help me use ChatGPT or similar GenAI tools effectively (e.g internet, documentation, tutorials)
	PBC4	Even if I struggle at first, I believe I can learn to use ChatGPT or similar GenAI tools effectively
Behavioral Intention	BIN1	I plan to use ChatGPT or similar GenAI tools regularly for my studies
	BIN2	Whenever I struggle with an academic task, I will consider using ChatGPT or similar GenAI tools
	BIN3	I would recommend the use of ChatGPT or similar GenAI tools for academic purposes to others