Artificial Intelligence in Student Learning: Balancing Usefulness, Stress, and Cognitive Load

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PREFACE

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KEYWORDS

Artificial intelligence, academic stress, cognitive workload, TAM, CLT, student well-being, higher education, digital literacy, institutional support

ABSTRACT

This thesis investigates how artificial intelligence (AI) tools influence academic well-being and cognitive workload among university students in the Netherlands. As AI becomes increasingly common in higher education, understanding its emotional and cognitive impact on students is crucial. Grounded in the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT), this study examines how perceived usefulness (PU), perceived ease of use (PEOU), and various types of cognitive load relate to academic stress. It also explores whether digital literacy, ethical clarity, and institutional support moderate these relationships.

Data were collected through a structured online survey completed by 70 university students across multiple disciplines. Descriptive statistics, correlation analysis, multiple regression, and moderation and mediation analyses using the PROCESS macro were conducted. The results show that perceived usefulness is a significant positive predictor of academic stress, revealing a performance pressure paradox. In contrast, cognitive load dimensions and institutional factors showed weaker or non-significant effects.

These findings suggest that while AI tools are perceived as beneficial, they may also heighten academic pressure, particularly among digitally literate students. The study emphasizes the psychological and institutional complexities of AI integration and calls for balanced implementation strategies that address both academic support and emotional well-being. Practical implications and directions for future research are discussed.

Table of Contents

1 Introduction

This chapter introduces the research by explaining how artificial intelligence (AI) tools are used in higher education and how they relate to academic stress among university students in the Netherlands. It describes the research problem, presents the research question, outlines the research design, and explains the importance of the study for both science and practical management.

1.1 Problem Indication

AI tools such as ChatGPT, Grammarly, and AI-powered academic planners are becoming increasingly popular among university students. Bancoro (2024) found that using AI tools positively influences academic performance in business administration students. This suggests that these tools may offer practical support that could reduce academic stress. However, their use can also bring psychological challenges. For example, Milinković and Vuleta (2024) noted that students often face ethical dilemmas related to academic integrity when using generative AI tools. These concerns can add to their stress.

Chea and Xiao (2024) explained that although AI-assisted tools help improve reading skills and vocabulary, relying on them too much could harm the development of critical thinking skills. Similarly, Jia and Tu (2024) pointed out that AI tools can make learning easier and improve motivation and confidence, but they may also reduce students' awareness of the need to think critically.

Rahim et al. (2023) emphasized that students may feel stress when trying to use AI tools with complex features. Irfan et al. (2023) added that unclear rules about how AI tools handle data can cause additional stress, especially when students do not fully understand how their information is collected or used.

Although several studies have highlighted that AI use can contribute to student stress (Milinković & Vuleta, 2024; Irfan et al., 2023; Chea & Xiao, 2024), these insights often remain surface-level or are drawn from broader contexts outside formal education. Additionally, many of these studies focus on performance outcomes rather than emotional consequences (Bancoro, 2024), or they emphasize general stress factors like academic workload without linking them to AI specifically (Kausar, 2010). Others recognize that emotional intelligence may mediate stress responses but stop short of exploring how AI tools interact with this dynamic (Khan & Siddiqui, 2024). Crucially, few studies use established theoretical frameworks to explain the mechanisms by which AI tool use may increase or reduce academic stress. Research rarely integrates behavioral models such as the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT), which can help reveal both adoption patterns and mental strain (Remegio & Asahid-Cheng, 2024; Sweller, 2011). Addressing this theoretical and contextual gap is essential for understanding whether AI tools genuinely support student well-being, or whether they introduce new challenges such as increased cognitive load, ethical ambiguity, or tool dependency.

1.2 Problem Statement

Despite the growing use of AI tools like ChatGPT, Grammarly, and AI-based planners in higher education, their effects on students' mental well-being have not been deeply explored. Many studies highlight the performance benefits of AI tools, such as better academic results and improved time management (Bancoro, 2024; Rahim et al., 2023), but fewer studies examine their influence on psychological outcomes, such as academic stress.

The current literature shows that students often have mixed emotional reactions when using AI tools. For example, depending too much on AI-generated content can lead to anxiety and concerns about whether the work is original (Aziz et al., 2024; Milinković & Vuleta, 2024). At the same time, issues related to data privacy and fairness can create additional stress, especially when students are unsure how their personal data is used (Irfan et al., 2023).

There are also concerns about the mental effort required to use these tools. Some researchers argue that AI tools reduce cognitive load by making tasks easier (Chea & Xiao, 2024). Others claim that confusing interfaces or vague feedback can increase stress and information overload (Ozfidan et al., 2024). Students who have lower digital skills or less experience with AI may find the tools more frustrating than helpful.

Another concern is how AI use may affect long-term academic independence and critical thinking. Students who rely too much on AI tools might develop habits that reduce their confidence in handling academic work on their own. This could also harm their ability to manage stress (Jia & Tu, 2024; Fošner, 2024).

Although these concerns are known, few studies have looked specifically at how AI tools influence stress levels in university students, particularly in the Dutch context. There is also a lack of studies that connect established behavioral models like the Technology Acceptance Model (TAM) with psychological theories such as Cognitive Load Theory (CLT) to explain emotional outcomes like stress. As a result, the mental, ethical, and cognitive effects of AI use are often studied separately. This creates a clear gap in the research. It is necessary to understand both the academic benefits of AI tools and their broader impact on student well-being and stress

1.3 Research Question

This thesis investigates how AI tools affect the academic well-being and mental workload of university students in the Netherlands. As AI becomes more common in higher education, it is important to explore how these tools influence students' emotions, mental effort, and learning behavior. The study uses two well-known frameworks: the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT). TAM helps explain how students' views on usefulness and ease of use shape their decision to use AI. CLT helps explore how mental effort and complexity influence stress. Together, these models allow for a full understanding of how AI affects academic well-being.

The main research question guiding this study is:

To what extent do AI tools influence academic well-being and cognitive workload among university students in the Netherlands?

To address this question, three sub-questions are formulated:

1. **How do AI tools affect students' academic well-being, including their perceived stress and emotional response to academic tasks?**
   This question examines the extent to which students feel emotionally supported or pressured when using AI tools. It considers whether perceived usefulness of AI contributes to reduced stress or if it introduces new expectations and pressures in academic settings.

2. **To what extent do AI tools influence cognitive workload and academic autonomy in learning tasks?**
   This sub-question investigates how AI tools affect students' mental effort and sense of control over learning. It focuses on whether AI tools simplify complex tasks, reduce unnecessary distractions, or potentially lead to overreliance and reduced autonomy.

3. **How do ethical and practical concerns about AI tools influence students' academic stress and mental workload?**
   This sub-question investigates whether uncertainty around ethical use, lack of institutional guidance, and varying levels of digital literacy create confusion, guilt, or decision fatigue, all of which may increase students' emotional strain and cognitive load when engaging with AI tools in academic tasks.

1.4 Research Design

This study uses a quantitative research design to explore how AI tools affect academic stress among university students in the Netherlands. A quantitative approach is suitable because it allows for the systematic collection and analysis of data from a large group. This provides measurable insights into patterns and relationships.

The study will involve an online survey with 100 to 200 university students from different academic fields in Dutch universities. The survey will include 20 to 30 multiple-choice questions to measure students' opinions on AI use, stress levels, academic performance, time management, and ethical concerns. These questions are based on tested psychological and behavioral concepts. A 5-point Likert scale will be used so students can express their level of agreement with each statement.

The data will be analyzed using SPSS software. The analysis includes descriptive statistics to summarize student characteristics and response patterns, Pearson correlations to explore relationships between key variables, and multiple regression analysis to identify predictors of academic stress. A moderation analysis will also be conducted using Hayes' PROCESS tool to test the role of ethical clarity in these relationships.

1.5 Contribution

This thesis contributes to both academic research and practical decision-making by examining how AI tools influence student well-being and mental workload. It combines the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT) to offer a more holistic view of student experiences with AI in higher education. The findings are expected to provide new theoretical insights into the emotional consequences of perceived usefulness and practical recommendations for policy makers and educators on how to support students using AI tools ethically and effectively.

1.6 Structure of the Thesis

This thesis is organized into six chapters, each addressing a specific component of the research on AI tool usage and its impact on academic well-being and cognitive workload among university students in the Netherlands.

Chapter 1 introduces the research topic, outlines the problem, defines the research questions, and explains the study's academic and practical relevance.

Chapter 2 provides a literature review on AI tools in education, perceived stress, and theoretical frameworks. It introduces the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT), which guide the study.

Chapter 3 details the research methodology, including the quantitative survey design, participant recruitment, operationalization of key variables, and the data analysis plan.

Chapter 4 presents the results, including descriptive statistics, correlation analysis, multiple regression, and moderation analysis.

Chapter 5 interprets the results in light of TAM and CLT, offering explanations for the findings and discussing their meaning for student experience and stress.

Chapter 6 concludes the thesis by summarizing the main findings and directly answering the research questions. It also discusses theoretical and practical contributions, study limitations, directions for future research, and implications for educational practice.

2 Literature review.

This chapter reviews relevant research to clarify how AI tools shape university students' academic well-being and cognitive workload. While applications like ChatGPT, Grammarly, and AI-based planners are widely used to support writing, planning, and studying (Ateeq et al., 2024; Sova et al., 2024), students' experiences vary. Some report improved productivity and engagement (Owusu et al., 2024), while others highlight challenges such as ethical uncertainty, overdependence, or stress caused by unclear guidelines (Lund et al., 2024; Abdulah et al., 2024).

To understand these mixed outcomes, this chapter focuses on three core areas: theoretical models that explain student interaction with AI tools, evidence on how AI affects academic stress, mental workload, and behavior, and emotional, ethical, and institutional factors that shape students' perceptions and use of AI tools. This review connects these strands to support the study's central question on how AI use affects academic well-being and cognitive effort in Dutch higher education.

Each section of this chapter contributes to answering the sub-questions presented in Chapter 1. Section 2.2 and 2.3 introduce TAM and CLT, which provide the theoretical basis for understanding how AI tools affect both academic stress and cognitive effort. Sections 2.4 through 2.8 explore the emotional, ethical, and institutional dimensions of AI use, examining how uncertainty, digital skills, and policy gaps influence students' stress and workload. The final sections synthesize research gaps and present the conceptual framework and hypotheses, linking theory to measurable outcomes.

2.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a common theory used to explain how people start using new technologies. It focuses on two beliefs: perceived usefulness (PU) and perceived ease of use (PEOU). These beliefs affect whether someone chooses to use a new tool (Davis, 1989). For university students, TAM helps explain why they choose to use AI tools like ChatGPT or Grammarly.

Recent studies show that TAM still explains how students engage with AI tools. Remegio and Asahid-Cheng (2024) found that perceived usefulness was the most important reason students adopted ChatGPT, especially in technical fields. This connects to the research gap by asking not just whether students use AI tools, but why, and whether this reduces or increases stress.

The link between stress and AI use is becoming clearer in TAM-based studies. Saif et al. (2024) found that stressed students were more likely to find AI tools helpful and use them more often. When students face tight deadlines or mental overload, they turn to AI tools to cope. This highlights the role of perceived usefulness in TAM.

Ease of use also matters, but less so among students who are already skilled with digital tools. Mustofa et al. (2025) found that while perceived usefulness stayed important, ease of use had little effect for students already familiar with AI tools. This means that the effect of ease of use may decrease as digital skills increase. This idea links TAM with the next theory, Cognitive Load Theory.

TAM is also expanding to include trust and ethics. Mustofa et al. (2025) added these factors to the model and found they influenced how students felt about using AI. Since this thesis focuses on academic well-being, this update is useful: trust and ethical clarity might affect how much AI tools actually help reduce stress. In this way, TAM does not only help explain tool adoption but also helps examine how adoption connects to stress and mental workload.

Overall, TAM supports this research by explaining how emotional, ethical, and personal factors influence the use of AI tools. While usefulness and ease of use remain important, this thesis goes further by exploring how these beliefs relate to academic well-being and stress.

2.2 Cognitive Load Theory (CLT)

Cognitive Load Theory (CLT) is a useful framework for understanding how mental effort affects learning, especially when technology is involved. CLT divides mental load into three types: intrinsic, extraneous, and germane. Intrinsic load is based on how complex the content is. Extraneous load comes from poor design or confusing instructions. Germane load refers to the mental effort needed to build useful knowledge structures (Sweller, 2011).

This theory is important for judging whether AI tools help students reduce or increase mental effort. Some research shows that AI tools lower extraneous load by offering easy access to useful information and fast feedback (Toh & Tasir, 2024). However, if these tools are difficult to use or not adapted to the student's level, they can increase stress (Khasawneh & Khasawneh, 2024).

For example, students using AI on mobile devices experienced lower cognitive load when the tools followed clear design rules like breaking content into parts or using multiple formats (Toh & Tasir, 2024). On the other hand, adaptive learning tools that did not match students' skills caused higher mental strain (Khasawneh & Khasawneh, 2024).

Stress also influences cognitive load. When students are anxious, their mental resources are reduced, making it harder to learn (Chen & Chang, 2009). This is important for the research question because it shows that while AI can reduce effort, it may also raise mental demands when used under stress or when ethical concerns are unclear. CLT helps this study examine how AI tool use contributes to changes in students' cognitive workload and emotional well-being, rather than how stress levels influence the use of AI tools.

CLT supports TAM by showing how AI tools affect students' thinking during learning. TAM focuses on students' attitudes and choices, while CLT explains what happens in their minds. Together, they provide a full picture of how AI use affects learning and stress.

While TAM and CLT were selected for their complementary strengths in explaining behavioral adoption and cognitive strain, other theoretical frameworks were considered. For example, the Unified Theory of Acceptance and Use of Technology (UTAUT) focuses on organizational settings and performance expectancy, which are more suited to workplace environments than individual academic well-being (Venkatesh et al., 2003). Self-Determination Theory (SDT) emphasizes psychological needs such as autonomy and intrinsic motivation (Deci & Ryan, 2000), but does not directly address cognitive workload or technology usability. In contrast, TAM and CLT offer a practical and psychological foundation to examine how AI tools impact students' mental effort, perceived stress, and emotional outcomes in higher education.

2.3 Ethical and Psychological Concerns with AI Tools

While AI tools can support academic tasks, their emotional and psychological effects are more complex than they first appear. Some studies suggest that these tools reduce stress by offering timely support. For example, Zhu (2024) found that fast feedback from AI systems helped students manage heavy workloads. Similarly, AI chatbots using therapy techniques have helped students feel more supported emotionally (De la Puente et al., 2024).

However, too much reliance on AI may weaken social connections. Crawford et al. (2024) found that using AI instead of talking to classmates or teachers reduced students' sense of belonging. This can lower performance and make students feel isolated. So, AI does not only affect tasks but also changes the emotional experience of learning.

Ethical uncertainty can also increase stress. When students are unsure about what AI use is allowed, they may feel guilt or anxiety, especially in schools without clear rules (Fošner, 2024). This fits with the research gap, especially in Dutch universities where policy is still developing.

How students respond emotionally to AI also depends on personal traits like confidence, motivation, and emotional intelligence. Students who are unsure about their tech skills may feel more stress when using AI (Khan & Siddiqui, 2024). This increases their mental and emotional burden.

AI tools affect more than just productivity. They change how students feel, how they stay motivated, and how much they trust their schools. Understanding these effects is important for building safe and supportive learning environments.

2.4 Ethical Considerations of AI use in higher education

As AI tools become more common in academic settings, ethical concerns have become a major issue in higher education. These concerns are especially relevant for university students, who are often the main users of tools like ChatGPT, Grammarly, and AI planning assistants. While these tools provide convenience and support, they also raise important questions about academic honesty, data privacy, fairness, and independent learning. These issues affect students not only on a policy level but also in their daily experience of stress, responsibility, and uncertainty, which connects directly to this study's focus on academic well-being.

One common issue in the literature is the lack of clear rules from universities on how AI tools can be used ethically in academic work. Irfan et al. (2023) found that many students work in a "grey area" where they are unsure if using AI to write, edit, or brainstorm ideas breaks academic rules. This confusion often leads to feelings of guilt and anxiety, especially when students believe they are using the tools responsibly but still fear being accused of misconduct.

Privacy is another major concern. AI platforms often collect large amounts of user data, and students may not be fully aware of how this data is stored or used. Zhai (2023) found that although many students recognize these risks, they still tend to choose efficiency over data protection. This raises concerns about digital awareness and informed decision-making. It also shows a gap between what the technology can do and what students understand about it, which may increase stress and reduce their overall sense of control.

Different academic fields and cultures also shape how students view AI ethics. For instance, Irfan et al. (2023) found that students in science and engineering worry more about data privacy than those in humanities or social sciences. This suggests that ethical concerns are not the same for every group. Zeer et al. (2023) argued that AI's ethical impact goes beyond plagiarism and includes bigger issues such as fairness, independence, and the relationship between students and teachers.

When there is no formal education or discussion about AI ethics, students are left to make these choices on their own. This increases both cognitive and emotional stress. Without guidance, students must decide for themselves what is acceptable, which can create uncertainty and pressure on top of regular academic demands.

Ethical issues in AI use are not just about policy. They have a real impact on students' mental health, confidence, and trust in the educational system, and addressing these concerns is necessary to create learning environments where AI supports, rather than harms, students' well-being.

2.5 Empirical evidence on AI tools, academic stress, and performance

Recent studies provide important insights into how AI tools affect academic stress, cognitive effort, and student performance. Although these tools are often created to reduce stress by improving efficiency, research shows that their impact depends on how they are used, the support provided by institutions, and the personal characteristics of the students.

On the positive side, AI applications such as chatbots and learning assistants have been shown to improve student well-being and reduce stress. For example, De la Puente et al. (2024) found that an AI chatbot based on cognitive behavioral therapy (CBT) lowered stress and anxiety in students while still being easy to use. This shows that AI tools, when well-designed, can help students manage their emotions, especially when they are based on proven psychological methods.

Similarly, Kien et al. (2024) found that students who used strategies like goal-setting and reflection while using AI tools reported lower stress and better academic results. This suggests that the benefits of AI depend not only on the technology itself, but also on how it fits into the student's overall learning approach. This idea supports the importance of cognitive workload and coping strategies in this research.

However, not all findings are positive. Sahu et al. (2024) and Talib and Zia-ur-Rehman (2012) both found that students with high academic stress tend to perform worse. This shows that AI tools may not always reduce stress, especially in situations where students feel pressure or uncertainty. When students see AI tools as shortcuts or are unsure if their use is allowed, it may lead to even more stress.

In addition, wearable AI technology has shown potential for monitoring stress, but its use in education is still limited. Abd-alrazaq et al. (2024) found that wearable AI devices could predict student stress with 85% accuracy. However, using this data to support students in real time is still in development.

These studies suggest that AI tools can support academic well-being and performance, but their success depends on several factors. These include clear university policies, students' ability to use the tools effectively, and whether students feel supported. These are the same areas that this study focuses on, as they remain underdeveloped in the current research.

2.6 Digital Literacy and Student Confidence

Digital literacy plays an important role in how university students use AI tools. As AI becomes more common in education, students' ability to use digital technologies, along with their confidence in doing so, strongly influences their stress levels, mental effort, and academic well-being. This connects directly to the research focus on the psychological and cognitive impact of AI use in higher education, especially in the Dutch context.

Several studies have shown that digital literacy is a key factor in accepting and effectively using AI tools. Börekci and Çelik (2024) found that students with higher levels of digital literacy were more likely to view AI tools as helpful and easy to use. These students were also more willing to use AI for academic tasks. This supports the ideas of the Technology Acceptance Model (TAM), which highlights perceived usefulness and ease of use as important factors in technology adoption.

However, digital literacy is not only about technical skills. It also includes the ability to create content, communicate online, and evaluate digital sources. Bui et al. (2025) found that many students believe they are good at online communication, but report lower confidence in creating original content or managing information. These skills are especially important for using AI tools in research and writing. When students lack confidence in these areas, they may feel more stress during academic tasks.

Digital literacy is also linked to emotional strength and independence. Zayed (2024) found that students with higher digital resilience, which is closely related to digital literacy, reported lower stress and greater well-being. In contrast, students with lower digital skills often felt more anxiety and were less confident in using AI tools, which led to more academic challenges.

Importantly, students' confidence with AI does not depend only on their own skills. The learning environment also plays a role. Akakpo (2024) and Chigwada (2024) suggested that universities and academic libraries should offer digital literacy training at the beginning of students' studies. Without formal guidance, many students rely on trial-and-error when using AI, which can increase stress and ethical uncertainty.

Digital literacy can either help or hinder students' use of AI tools. When students have strong digital skills, they are more independent and less stressed. When these skills are missing, students may feel confused or overwhelmed, which adds to the well-being concerns that this study aims to address.

2.7 Institutional guidelines and ambiguity

The rapid growth of artificial intelligence (AI) tools in higher education has happened faster than the development of clear university policies. This delay in policy-making creates confusion and stress for students, who are often unsure how to use AI tools in academic work. Since this study focuses on how AI affects academic well-being and mental effort, institutional clarity becomes an important factor.

Recent studies show that universities differ widely in how they manage AI. Atkinson-Toal and Guo (2024) found that in the United Kingdom, some universities actively support AI use with clear policies and training, while others provide little guidance or even restrict it. This inconsistency means students often work in unclear situations, which increases anxiety and uncertainty.

This problem is not limited to the UK. At Kherson State University, Spivakovsky et al. (2023) found that even when universities had AI policies, they were often not well communicated, limited to specific fields, or unclear in their meaning. Many students did not know if using AI for editing, brainstorming, or support was acceptable. As a result, students often followed peer habits instead of relying on official rules. This adds extra mental effort, as students have to think about what is allowed while managing their regular academic tasks.

Student feedback supports these findings. In a global survey, Al Zaidy (2024) found that although 86% of students used AI tools, only 5% were fully aware of their university's rules about AI. Also, 72% of students said they wanted more help from their institutions in the form of AI training and ethical guidelines. Without such support, many students felt guilty, stressed, or unsure if their actions were correct.

In the United States, Oh and Sanfilippo (2024) found that universities with clear AI policies had students who reported higher levels of trust and lower academic stress. Their study suggests that involving students in policy-making, teaching AI ethics in class, and ensuring consistent communication between departments can help reduce stress and confusion.

Unclear or missing policies are not just administrative problems. They directly affect how students feel, how confident they are in their choices, and how much mental effort they must spend on navigating AI use. This shows that clear institutional guidance is necessary to reduce stress and improve students' academic experience with AI.

2.8 Existing research gap

Although AI tools are being used more often in higher education, there is still a large gap in understanding how they affect students' mental well-being and cognitive effort, especially in real academic settings. While many studies explore how AI improves academic performance and engagement (Fazil et al., 2024), fewer focus on how these tools affect stress, thinking effort, or ethical decision-making. This is especially true for university students who use AI tools regularly for studying and assignments.

First, current research on AI and academic stress often looks only at outcomes such as grades or satisfaction. These studies do not explore how AI use affects stress levels or mental effort in different learning situations (De la Puente et al., 2024; Khasawneh & Khasawneh, 2024). As a result, it is unclear whether AI tools actually reduce students' workload or simply create new sources of pressure, such as decision fatigue, dependency, or uncertainty about what is acceptable.

Second, while theories like the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT) are useful, they are rarely used together to study stress and well-being. TAM explains why students adopt AI tools, and CLT helps describe how learning demands create mental load. However, few studies have linked these models to real indicators of well-being, such as stress, overload, or emotional strain. This study aims to fill that gap by using both models not only to understand usage, but also to examine how AI affects emotional outcomes.

Third, very little research has been done in the Dutch university system. Cultural, institutional, and legal differences can shape how students experience and understand AI. In the Netherlands, many universities still lack clear AI guidelines, which means students often face unclear expectations. This lack of structure can increase cognitive load and emotional stress (Sayed et al., 2024), especially when students must make ethical decisions without guidance.

Finally, many studies ignore individual factors that affect how students use AI. Personal characteristics such as digital literacy, ethical awareness, and emotional strength all shape whether AI tools reduce or increase stress. For example, one student may find AI helpful and calming, while another may feel anxious and unsure. These differences are rarely explored in detail, especially in the Dutch context, where universities often have decentralized policies. This makes it hard for students to know what is allowed and adds to their mental and emotional burden.

This study addresses these gaps by examining how AI tools affect academic well-being and mental workload using TAM and CLT, while also considering ethical, psychological, and institutional factors. It adds new knowledge to the conversation about how prepared universities are for the ethical and emotional impact of AI on students.

2.9 Conceptual Framework and Model

This study uses a conceptual framework that combines two theoretical models: the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT). These models help explain how AI tools influence students' academic well-being and mental workload. In addition, the framework includes real-life factors such as digital literacy, ethical clarity, and institutional support. These factors are expected to shape how students experience AI tools in their academic work.

2.9.1 Core Constructs

1. **Technology Acceptance Model (TAM)**
   - **Perceived Usefulness (PU)**: The extent to which students believe AI tools enhance academic performance.

- **Perceived Ease of Use (PEOU)**: The degree to which students find AI tools easy to learn and use.

These two beliefs influence students' willingness to use AI, which in turn leads to actual usage.

2. **Cognitive Load Theory (CLT)**
   - **Intrinsic Load**: Tied to task complexity.
   - **Extraneous Load**: Caused by unclear AI interfaces or confusing academic policies.
   - **Germane Load**: The cognitive effort directed toward meaningful learning using AI.
3. **Psychological and Institutional Moderators**
   - **Digital Literacy & Confidence**: Affects students' ability to use AI tools effectively.
   - **Ethical Clarity**: This reduces stress caused by fear of making ethical mistakes.
   - **Institutional Support**: Availability of guidelines, training, and policy alignment.

2.9.2 Outcome Variables

- **Academic Well-Being**: Includes perceived academic stress, emotional resilience, and satisfaction.
- **Cognitive Workload**: The mental burden experienced while using AI tools during academic activities.

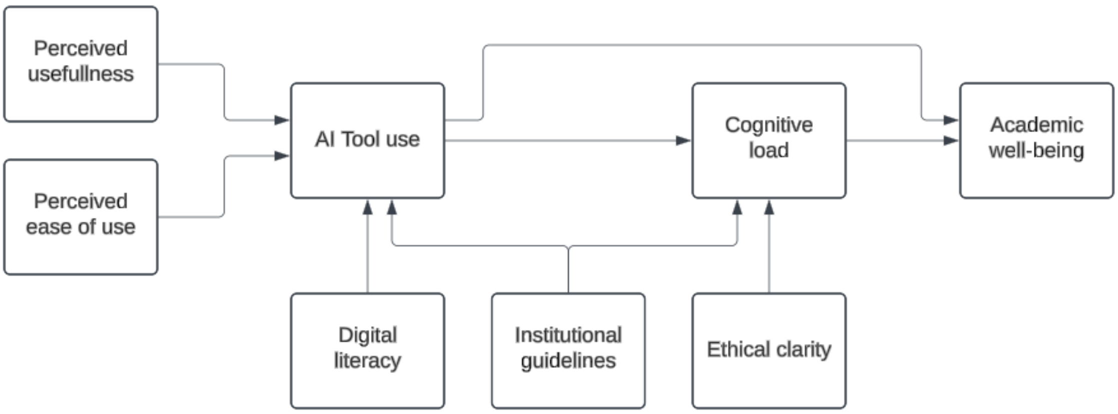

Figure 1: Conceptual model

Hypotheses:

H1: *Perceived Usefulness (PU)* of AI tools is positively associated with AI tool usage.

Students are more likely to use AI tools when they believe these tools enhance academic performance (Remegio & Asahid-Cheng, 2024).

H2: *Perceived Ease of Use (PEOU)* of AI tools is positively associated with AI tool usage.

Students who find AI tools easy to use are more inclined to adopt them (Mustofa et al., 2025).

H3: *AI tool usage* is negatively associated with cognitive load.

When used effectively, AI tools can reduce extraneous load by simplifying task demands (Toh & Tasir, 2024).

H4: *AI tool usage* is positively associated with academic well-being.

Strategic use of AI can reduce stress and increase students' perceived control over academic tasks (De la Puente et al., 2024).

H5: *Digital Literacy* moderates the relationship between AI tool usage and cognitive load.

High digital literacy reduces the extraneous load caused by navigating AI tools (Börekci & Çelik, 2024).

H6: *Ethical Clarity* moderates the relationship between AI tool usage and academic well-being.

Unclear AI policies may increase anxiety and guilt, undermining well-being (Fošner, 2024).

H7: *Institutional Guidelines* moderate the relationship between AI usage and both cognitive load and academic well-being.

Clear institutional policies reduce uncertainty, which improves both psychological and cognitive outcomes (Atkinson-Toal & Guo, 2024).

Hypothesis Code	Hypothesis Statement	Relationship Type	Source / Theoretical Basis
H1	Perceived Usefulness (PU) of AI tools is positively associated with AI tool usage.	Direct	Technology Acceptance Model (TAM) (Remegio & Asahid-Cheng, 2024)
H2	Perceived Ease of Use (PEOU) of AI tools is positively associated with AI tool usage.	Direct	Technology Acceptance Model (TAM) (Mustofa et al., 2025)
H3	AI tool usage is negatively associated with cognitive load.	Direct	Cognitive Load Theory (CLT) (Toh & Tasir, 2024)
H4	AI tool usage is positively associated with academic well-being.	Direct	Cognitive-behavioral stress models (De la Puente et al., 2024)
H5	Digital literacy moderates the relationship between AI tool usage and cognitive load.	Moderating	Digital literacy theory (Börekci & Çelik, 2024)
H6	Ethical clarity moderates the relationship between AI tool usage and academic well-being.	Moderating	Ethics in AI education (Fošner, 2024)
H7	Institutional guidelines moderate the relationship between AI usage and both cognitive load and academic well-being.	Moderating	Institutional policy research (Atkinson-Toal & Guo, 2024)

Table 1: Overview of Hypotheses

3 Methodology.

This chapter explains the research methods used to examine how AI tools affect academic well-being and mental workload among university students in the Netherlands. Based on the frameworks discussed in Chapter 2, this study uses a quantitative design, guided by the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT). These models are not only useful for explaining general adoption behavior but also offer specific constructs, such as perceived usefulness, extraneous load, and germane load, that can be measured to quantify students' academic stress and cognitive workload in relation to AI use.

While tools like ChatGPT and Grammarly are widely adopted for their learning benefits, few studies systematically explore how their use impacts different types of cognitive load or ethical ambiguity in real academic settings (Dahri et al., 2024; Kok et al., 2024). This study addresses this gap by combining TAM and CLT into a single quantitative framework that links behavioral intentions with measurable emotional and cognitive outcomes. The methodology is designed to uncover how specific aspects of AI tool usage, such as ease of use, perceived stress, or lack of ethical clarity, influence students' overall academic well-being.

This chapter describes the research design, the data collection methods, the sampling strategy, and the analytical techniques used. It also outlines the ethical steps taken to protect participants' privacy and ensure academic quality.

3.1 Research Design

This study uses a quantitative, cross-sectional design to explore how AI tools affect students' academic well-being and cognitive workload. Cross-sectional studies are widely used in education and psychology to investigate how multiple variables relate at a single point in time, making them well suited for measuring constructs like stress, cognitive load, and technology acceptance (Creswell & Creswell, 2018; Sedgwick, 2014). This approach enables the researcher to capture relationships among key variables from the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT), aligned with the main research question: To what extent do AI tools influence academic stress and mental demands among university students in the Netherlands?

A quantitative approach allows for analysis across a larger population, improving the reliability and generalizability of findings. Previous research using TAM shows that perceived usefulness and ease of use strongly influence how students adopt digital learning tools (Dahri et al., 2024). CLT adds further insight by evaluating students' mental effort through intrinsic, extraneous, and germane types of cognitive load, which is essential for understanding how AI tools impact academic stress and cognitive performance (Martella et al., 2024; Sandoval-Medina et al., 2024).

In addition, the study examines moderating variables such as digital literacy, ethical clarity, and institutional support. These contextual factors are known to shape student responses to AI use in higher education, especially in terms of stress and mental workload (Kok et al., 2024; Rahim et al., 2023; Fošner, 2024). While other research designs, such as longitudinal or qualitative methods, could offer deeper insights into long-term impacts, the cross-sectional design provides a timely and efficient snapshot of current student experiences and perceptions.

The survey used in this research is structured around validated TAM and CLT constructs. The next section details the sampling methods and data collection procedures.

3.2 Data Collection

3.2.1 Target Population and Sampling Strategy

The target population includes university students enrolled in higher education institutions across the Netherlands. These students come from different academic programs and study levels. As frequent users of AI tools like ChatGPT, Grammarly, and digital planners, they are well-suited to reflect on how these technologies affect their academic and psychological experiences.

A non-probability convenience sampling method was used to recruit participants. This involved sharing the survey through university mailing lists, social media platforms, and student organizations. While this method may limit how broadly the findings can be applied, it offers practical advantages in reaching a diverse student population quickly, which is suitable for exploring a relatively new topic.

The goal was to collect between 100 and 200 responses. This sample size is large enough to carry out statistical tests such as regression and correlation, and also allows for group comparisons, for example by study program or level of AI usage. Similar sample sizes have been used in past TAM and CLT based studies in education (Dahri et al., 2024; Maričić et al., 2025).

3.2.2 Survey Instrument Design

Data was collected using a structured online questionnaire, created with Qualtrics. The survey was tested by a small pilot group of 5 to 10 students to check for clarity and length. Qualtrics was selected for its strong privacy settings and flexible design features.

The questionnaire included four main sections:

1. **AI Tool Usage and Perception**
   Measures the frequency and type of AI tool usage, as well as students' perceived usefulness (PU) and perceived ease of use (PEOU), using validated TAM items (Davis, 1989; Dahri et al., 2024).

2. **Academic Well-Being and Stress**
   Utilizes adapted items from the Perceived Stress Scale (PSS) to measure how academic tasks impact student well-being when AI tools are involved.

3. **Cognitive Load**
   Includes items based on Cognitive Load Theory, distinguishing between intrinsic, extraneous, and germane load dimensions (Sandoval-Medina et al., 2024). Items probe how mentally taxing students perceive AI-mediated academic tasks to be.

4. **Ethical and Institutional Moderators**
   Captures students' perceptions of ethical clarity, data privacy, and trust in AI, as well as their awareness of institutional AI usage policies.

All items were rated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Responses were coded numerically for statistical analysis.

To reach a diverse student sample, the survey was distributed through multiple online platforms, including LinkedIn, WhatsApp, and Reddit. These platforms were selected to maximize outreach among university students and recent graduates across various fields of study. A snowball sampling method was encouraged by asking participants to share the survey link within their networks.

3.2.3 Survey Structure

To provide additional clarity on the organization of the survey, an overview of the questionnaire sections, the theoretical constructs measured, and the number of items per construct is presented below in table 2. This structure makes sure that each dimension of the conceptual framework, spanning TAM, CLT, academic stress, and moderating factors, is systematically captured through validated or adapted survey items.

Survey Section	**Construct**	**Number of Items**
Section 1: Background information	Demographics	3
Section 2: AI Usage and Perception	Perceived Usefulness	4
	Perceived Ease of Use	2
	Behavioral Intention to Use AI	1
	AI Usage Frequency	1
Section 3: Cognitive Load	Intristic Load	2
	Extraneous Load	3
	Germane Load	2
Section 4: Academic Stress and Well-being	Academic Stress and Coping	4

Section 5: Moderators	Digital Literacy	2
	Ethical Literacty	2
	Institutional Support	2
Section 6: Final Reflection	Overall Impression of AI Impact	1

Table 2: Summary of the survey sections, theoretical constructs, and number of items included in the questionnaire.

3.3 Data Analysis

The data collected through the survey will be analyzed using IBM SPSS Statistics, following a multi-step procedure aimed at answering the central research question: *To what extent do AI tools influence academic well-being and cognitive workload among Dutch university students?* Statistical techniques are selected to test the conceptual relationships derived from TAM, CLT, and related psychological and institutional moderators.

3.3.1 Data Cleaning and Preparation

Before analysis, the data was checked and cleaned. Responses with too many missing answers or signs of inattention, such as selecting the same option throughout, were removed. Likert-scale responses were converted to numbers, and some were reverse-coded as needed.

Cronbach's alpha was used to test the reliability of grouped items, such as those measuring perceived usefulness or academic stress. A value of 0.70 or higher was considered acceptable, following standards in information systems research (Venkatesh et al., 2003).

3.3.2 Descriptive Statistics

Initial descriptive statistics (means, medians, standard deviations, and frequency distributions) will be calculated to summarize participants' demographic characteristics, AI tool usage patterns, and average ratings across constructs such as perceived usefulness, cognitive load, and academic stress. These insights provide an empirical overview of how AI tools are currently perceived and used in higher education contexts.

3.3.3 Inferential Statistics

Pearson correlation analysis was used to explore the strength and direction of relationships between key continuous variables. This included relationships among perceived usefulness and ease of use of AI tools, different types of cognitive load, academic stress, digital literacy, ethical clarity, and institutional support. These correlations helped test the main hypotheses and identify meaningful associations for further regression and moderation analyses.

3.3.4 Regression analysis

Multiple linear regression was used to examine whether perceived usefulness, ease of use, cognitive load, and support-related variables predicted academic stress. The analysis tested the explanatory power of Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT) variables.

Hayes' PROCESS macro for SPSS was used to conduct moderation analyses (Model 1), testing whether digital literacy, ethical clarity, or institutional support moderated the relationship between AI perceptions and academic stress. In addition, serial mediation models (Model 6) were run to assess whether AI tool usage and cognitive load sequentially mediated the effects of perceived usefulness and ease of use on academic stress.

This approach followed established practices in TAM and CLT research, including those used by Venkatesh et al. (2003) and Maričić et al. (2025).

3.3.5 Visualization of the results

Key results will be presented using tables, and where appropriate, graphs or boxplots. These visualizations will support interpretation of statistical patterns and highlight key findings such as differences in cognitive load by user type or predictors of academic stress.

3.4 Ethical Considerations

Ethical integrity is central to this research, particularly given the study's focus on students' psychological states, cognitive stress, and perceptions of academic integrity in relation to AI tools. To ensure validity, the survey instrument was based on theoretical constructs from TAM and CLT, using previously validated items from peer-reviewed studies (Davis, 1989; Sandoval-Medina et al., 2024). A small pilot test ($n = 5–10$) was conducted to assess clarity and question relevance. Reliability was tested through Cronbach's alpha to confirm internal consistency of multi-item scales, with a threshold of 0.70 considered acceptable (Venkatesh et al., 2003).

To avoid bias, questions were neutrally worded, and participants were assured of anonymity and confidentiality to reduce social desirability effects. Sampling bias was mitigated through distribution across diverse online platforms and student groups. All responses were voluntary, and participants could withdraw at any point without consequence.

3.4.1 Informed Consent and Voluntary Participation

Participants will be informed about the study's purpose, and rights through a digital informed consent form displayed at the start of the online survey. Participation is entirely voluntary, and respondents may withdraw at any time without explanation or penalty.

3.4.2 Anonymity and Data Privacy

To ensure anonymity, no personally identifiable information (e.g., name, email, institution, or IP address) will be collected. Survey responses will be stored securely on the researcher’s computer and will be accessible only to the primary researcher. All data will be used exclusively for academic purposes and will be permanently deleted after the thesis is graded and archived.

This research follows ethical guidelines to protect participants’ privacy, uphold informed consent, and ensure voluntary participation. Before starting the survey, participants will be provided with a digital informed consent form outlining the study’s purpose, the nature of their involvement, and their rights.

Participation will be entirely voluntary. Respondents may withdraw at any time without explanation or consequence. Participants will not be asked to disclose any identifying information such as names, student numbers, or institutional affiliations.

The data collected will be used solely for analyzing patterns related to AI tool usage, academic stress, and cognitive workload. It will not be shared with any third parties.

3.5 Use of AI

ChatGPT and Grammarly were used during the writing process to improve clarity, structure, and language. These tools supported editing and idea refinement but were not involved in generating content. All research decisions and academic contributions were made independently by the researcher. This statement ensures transparency while confirming the originality of the work.

4 Results.

This chapter presents the results of the statistical analyses conducted to address the central research question: *To what extent do AI tools influence academic well-being and cognitive workload among Dutch university students?*

The results are organized into several sections. First, descriptive statistics are presented to provide an overview of the sample demographics, AI tool usage patterns, and average scores for key constructs. Next, inferential statistics including Pearson correlation analysis are used to explore relationships among variables. Finally, multiple regression, moderation, and mediation analyses are conducted to test the predictive relationships and conditional effects proposed in the conceptual model.

4.1 Sample Demographics

This study included 70 university students from different academic programs in the Netherlands. Most participants were between 25 and 34 years old (51.4%), followed by those aged 18 to 24 (42.9%). A smaller number of students were aged 35 to 44 (4.3%), and only one participant (1.4%) was in the 45 to 54 age range (see Figure 2). This means that the sample mainly reflects young adult students, who are likely to be in undergraduate or master's programs. Their stage in education could affect how they view and use AI tools in academic settings.

Looking at gender, the majority of respondents identified as male (58.6%), followed by female (37.1%). A small number identified as non-binary or third gender (2.9%), and one student (1.4%) preferred not to say (see Figure 3). This gender imbalance could influence the results. For example, past research has found that men and women sometimes differ in how they handle academic stress and how comfortable they feel with using digital tools like AI (Venkatesh & Morris, 2000). Because of this, the findings might reflect the experiences of male students more strongly than others.

The students came from a range of academic fields. Most were enrolled in Business, Economics, or Management programs (38.6%). Other common fields were Computer Science (14.3%) and Medicine or Health Services (10.0%). Smaller numbers came from Humanities (8.6%), Law (7.1%), Social Sciences (7.1%), and Engineering (5.7%). There were also single participants from Communication, Arts and Design, Environmental Studies, Mathematics, and Natural Sciences (see Figure 4). Since a large portion of the sample studies business, tech, or health-related subjects, the results may be more relevant to those fields where AI tools are more often used in education.

The sample includes a mix of age groups, genders, and study backgrounds. However, some groups are more strongly represented than others. These patterns should be kept in mind when interpreting the findings, especially because factors like age, gender, and study program may affect how students experience AI in their academic work.

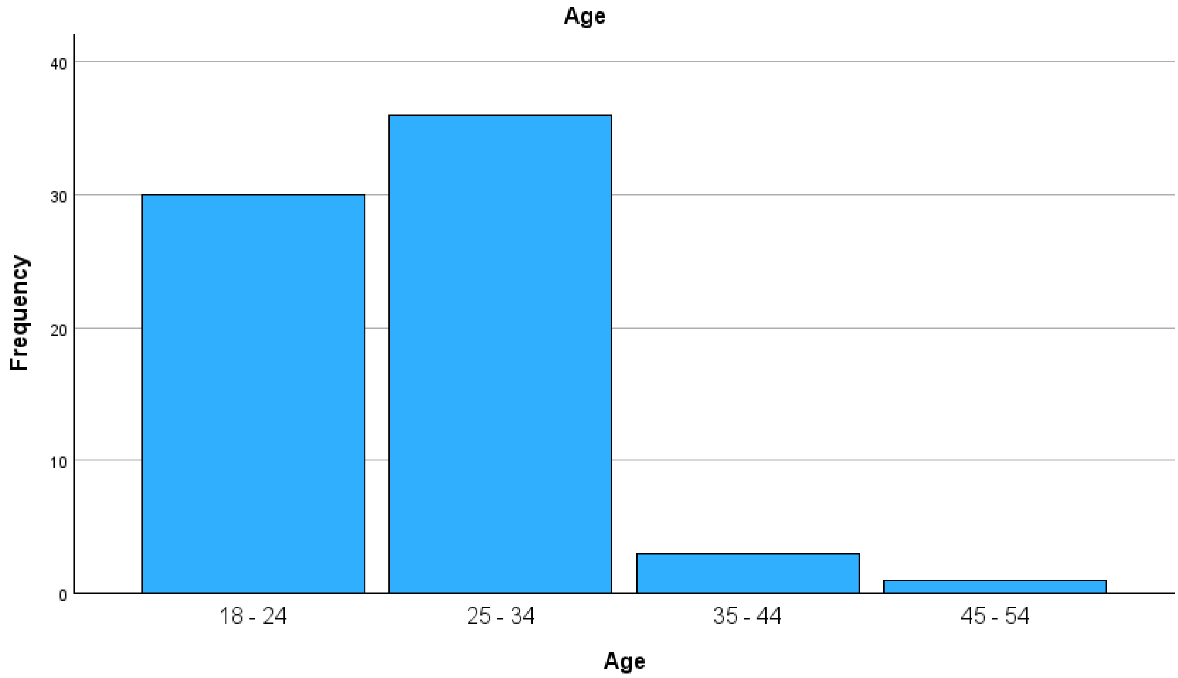

Figure 2: Age distribution of university student participants (N = 70).

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18 - 24	30	42.9	42.9	42.9
	25 - 34	36	51.4	51.4	94.3
	35 - 44	3	4.3	4.3	98.6
	45 - 54	1	1.4	1.4	100.0
	Total	70	100.0	100.0	

Table 3: Age distribution of university student participants (N = 70).

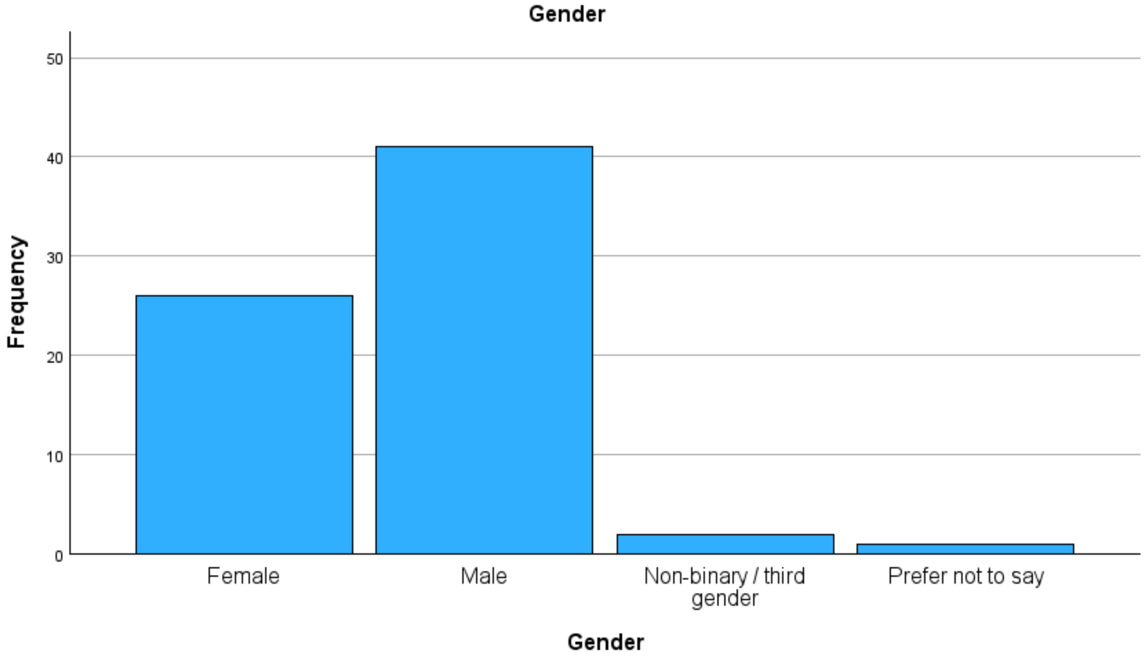

Figure 3: Gender distribution of university student participants (N = 70).

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	26	37.1	37.1	37.1
	Male	41	58.6	58.6	95.7
	Non-binary / third gender	2	2.9	2.9	98.6
	Prefer not to say	1	1.4	1.4	100.0
	Total	70	100.0	100.0	

Table 4: Gender distribution of university student participants (N = 70).

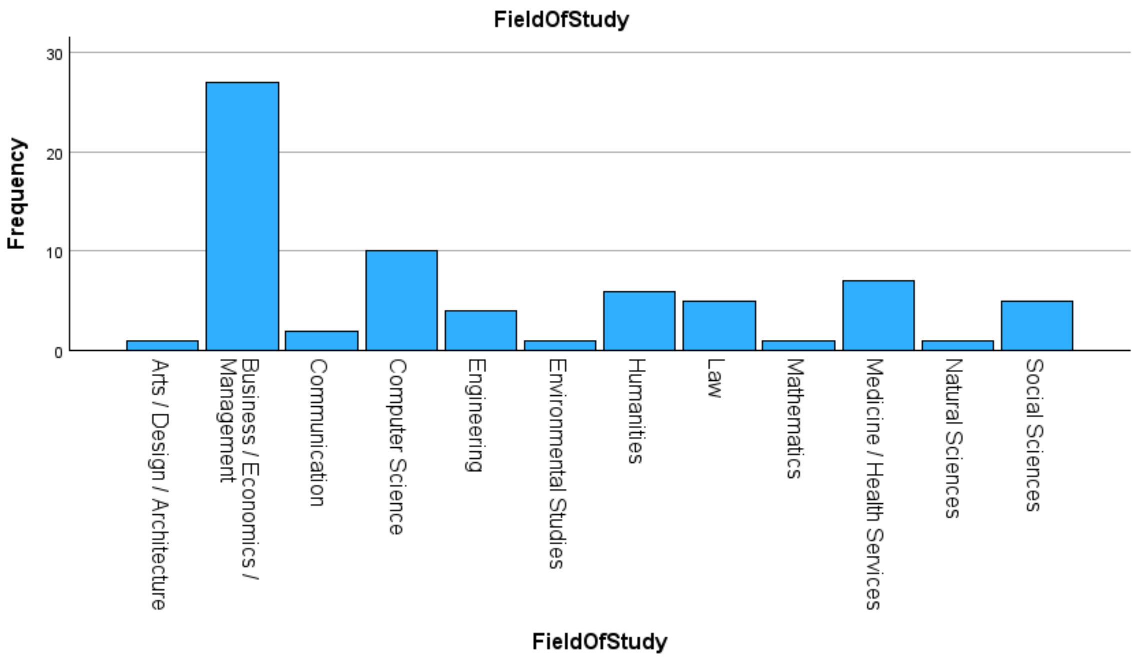

Figure 4: Distribution of students across academic fields of study (N = 70).

FieldOfStudy

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Arts / Design / Architecture	1	1.4	1.4	1.4
	Business / Economics / Management	27	38.6	38.6	40.0
	Communication	2	2.9	2.9	42.9
	Computer Science	10	14.3	14.3	57.1
	Engineering	4	5.7	5.7	62.9
	Environmental Studies	1	1.4	1.4	64.3
	Humanities	6	8.6	8.6	72.9
	Law	5	7.1	7.1	80.0
	Mathematics	1	1.4	1.4	81.4
	Medicine / Health Services	7	10.0	10.0	91.4
	Natural Sciences	1	1.4	1.4	92.9
	Social Sciences	5	7.1	7.1	100.0
	Total	70	100.0	100.0	

Table 5: Distribution of students across academic fields of study (N = 70).

4.2 Descriptive Analysis

Table 6 presents the descriptive statistics for the main constructs measured in this study. These include academic stress, the three types of cognitive load, perceptions of AI tools, digital literacy, ethical clarity, institutional support, and students' overall impressions of AI's impact.

Students reported a moderate level of academic stress (M = 3.32, SD = 0.62). The intrinsic load (M = 3.31, SD = 0.84) and extraneous load (M = 3.18, SD = 0.81) associated with academic tasks were also moderate, while germane load showed a slightly higher mean (M = 3.58, SD = 1.02), suggesting that students somewhat engage with meaningful learning processes.

Perceptions of AI tools were generally positive:

- Perceived Usefulness (PU) had a high mean (M = 4.79, SD = 0.82).
- Perceived Ease of Use (PEOU) was also rated highly (M = 4.06, SD = 0.91).

Regarding digital competencies and institutional support:

- Students reported relatively high digital literacy (M = 4.02, SD = 0.83).
- However, ethical clarity (M = 2.96, SD = 1.09) and institutional support (M = 2.96, SD = 1.09) were notably lower, suggesting that students perceive a lack of clear guidance regarding AI usage.

The overall impact of AI tools was perceived positively (M = 4.09, SD = 0.97).

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
AcademicStress_Mean	70	1.00	4.50	3.3214	.61700
IntrinsicLoad_Mean	70	1.00	5.00	3.3143	.84344
ExtraneousLoad_Mean	70	1.33	4.67	3.1810	.81390
GermaneLoad_Mean	70	1.00	5.00	3.5786	1.01666
PU_Mean	70	1.75	5.75	4.7893	.81942
PEOU_Mean	70	1.00	5.00	4.0643	.91256
DigitalLiteracy_Mean	70	1.50	5.00	4.0214	.82723
EthicalClarity_Mean	70	1.00	5.00	2.9571	1.09261
InstitutionalSupport_Mean	70	1.00	5.00	2.9571	1.09261
OverallImpact	70	2	5	4.09	.974
Valid N (listwise)	70				

Table 6: Descriptive statistics (means and standard deviations) for main study constructs (N = 70).

4.2.1 Reliability Analysis

A reliability analysis was conducted using Cronbach's Alpha to test the internal consistency of the survey instrument. The analysis produced a value of α = 0.694 across 22 items, which is slightly below the commonly accepted threshold of 0.70 (Table 7). This indicates moderate reliability of the scales used to measure the main constructs.

Reliability Statistics

Cronbach's Alpha	N of Items
.694	22

Table 7: Reliability Statistics for Survey Items (N = 70)

4.3 Correlation Analysis

Table 8 presents the Pearson correlation coefficients among the main study variables. The results are interpreted below according to the hypotheses developed in Chapter 2.

H1: Perceived Usefulness (PU) is positively associated with AI Tool Use.
PU showed a strong positive correlation with germane cognitive load ($r = .66$, $p < .001$), suggesting that students who find AI tools useful also tend to engage more deeply with academic tasks. Additionally, PU was positively correlated with AI tool usage frequency and perceived ease of use, supporting the idea that usefulness is a key driver of engagement. These results provide strong support for H1.

H2: Perceived Ease of Use (PEOU) is positively associated with AI Tool Use.
PEOU was significantly positively correlated with digital literacy ($r = .36$, $p = .002$) and perceived usefulness ($r = .43$, $p < .001$), indicating that students who find AI tools easier to use are more confident in using them and more likely to perceive them as useful. These patterns align well with the Technology Acceptance Model and support H2.

H3: AI Tool Use is negatively associated with Cognitive Load.
Extraneous load, which refers to unnecessary mental effort caused by unclear instructions or systems, was negatively correlated with PU ($r = -.25$, $p = .040$) and PEOU ($r = -.30$, $p = .011$). This means students who find AI tools useful and easy to use are less likely to experience confusion or overload, partially confirming H3. However, germane load, which is the mental effort invested in learning, was positively correlated with both PU and PEOU, indicating that AI tools might increase productive cognitive engagement rather than simply reduce mental effort.

H4: AI Tool Use is positively associated with Academic Well-Being.
Perceived usefulness had a strong positive correlation with lower academic stress ($r = .59$, $p < .001$), and PEOU also showed a significant positive association with well-being ($r = .25$, $p = .038$). Furthermore, digital literacy correlated with overall perceived AI impact ($r = .34$, $p = .004$). These findings suggest that students who feel confident using AI tools, and find them helpful and easy to use, tend to report better academic well-being, providing support for H4.

H5–H7 (Moderation Hypotheses)
Moderation effects involving ethical clarity, institutional support, and digital literacy are tested using PROCESS in Section 4.5. Correlation analysis is not sufficient to examine interaction effects and is therefore not used to evaluate H5 through H7.

Overall, these findings offer solid support for hypotheses H1 through H4, while also highlighting the nuanced role of cognitive load. Specifically, AI tools may reduce confusion (extraneous load) while promoting meaningful engagement (germane load), depending on how students perceive and use them. These patterns justify further analysis through regression, mediation, and moderation models in the sections that follow.

Correlations

		AcademicStress_Mean	IntrinsicLoad_Mean	ExtraneousLoad_Mean	GermaneLoad_Mean	PU_Mean	PEOU_Mean	DigitalLiteracy_Mean	EthicalClarity_Mean	InstitutionalSupport_Mean	OverallImpact
AcademicStress_Mean	Pearson Correlation	1	.277*	-.110	.496**	.587**	.249*	.118	.021	.021	.158
	Sig. (2-tailed)		.020	.363	<.001	<.001	.038	.332	.865	.865	.190
	N	70	70	70	70	70	70	70	70	70	70
IntrinsicLoad_Mean	Pearson Correlation	.277*	1	.120	.123	.171	-.017	-.077	-.103	-.103	-.024
	Sig. (2-tailed)	.020		.322	.311	.158	.888	.525	.396	.396	.841
	N	70	70	70	70	70	70	70	70	70	70
ExtraneousLoad_Mean	Pearson Correlation	-.110	.120	1	-.315**	-.246*	-.302*	-.185	-.276*	-.276*	-.148
	Sig. (2-tailed)	.363	.322		.008	.040	.011	.125	.021	.021	.222
	N	70	70	70	70	70	70	70	70	70	70
GermaneLoad_Mean	Pearson Correlation	.496**	.123	-.315**	1	.655**	.252*	.222	-.039	-.039	.205
	Sig. (2-tailed)	<.001	.311	.008		<.001	.035	.065	.747	.747	.088
	N	70	70	70	70	70	70	70	70	70	70
PU_Mean	Pearson Correlation	.587**	.171	-.246*	.655**	1	.425**	.258*	-.170	-.170	.264*
	Sig. (2-tailed)	<.001	.158	.040	<.001		<.001	.031	.159	.159	.028
	N	70	70	70	70	70	70	70	70	70	70
PEOU_Mean	Pearson Correlation	.249*	-.017	-.302*	.252*	.425**	1	.358**	.072	.072	.328**
	Sig. (2-tailed)	.038	.888	.011	.035	<.001		.002	.554	.554	.006
	N	70	70	70	70	70	70	70	70	70	70
DigitalLiteracy_Mean	Pearson Correlation	.118	-.077	-.185	.222	.258*	.358**	1	.085	.085	.339**
	Sig. (2-tailed)	.332	.525	.125	.065	.031	.002		.483	.483	.004
	N	70	70	70	70	70	70	70	70	70	70
EthicalClarity_Mean	Pearson Correlation	.021	-.103	-.276*	-.039	-.170	.072	.085	1	1.000**	.242*
	Sig. (2-tailed)	.865	.396	.021	.747	.159	.554	.483		<.001	.044
	N	70	70	70	70	70	70	70	70	70	70
InstitutionalSupport_Mean	Pearson Correlation	.021	-.103	-.276*	-.039	-.170	.072	.085	1.000**	1	.242*
	Sig. (2-tailed)	.865	.396	.021	.747	.159	.554	.483	<.001		.044
	N	70	70	70	70	70	70	70	70	70	70
OverallImpact	Pearson Correlation	.158	-.024	-.148	.205	.264*	.328**	.339**	.242*	.242*	1
	Sig. (2-tailed)	.190	.841	.222	.088	.028	.006	.004	.044	.044	
	N	70	70	70	70	70	70	70	70	70	70

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 8: Pearson correlation matrix showing relationships among academic stress, cognitive load dimensions, AI perceptions, digital literacy, ethical clarity, and institutional support (N = 70).

4.4 Regression Analysis

A multiple regression analysis was performed to determine whether cognitive load, AI tool perceptions, digital literacy, ethical clarity, and institutional support could predict academic stress (table 9).

The overall model was significant, $F(7, 62) = 6.45$, $p < .001$, and explained 42.1% of the variance in academic stress ($R^2 = .421$, Adjusted $R^2 = .356$).

Only perceived usefulness (PU) was a significant predictor of academic stress ($\beta = .471$, $p = .002$). This suggests that students who viewed AI tools as more useful also reported higher stress levels.

None of the other predictors, including PEOU, intrinsic load, extraneous load, germane load, digital literacy, or institutional support, were statistically significant ($p > .05$).

No problems with multicollinearity were detected, as all VIF values were below 2.2.

These findings suggest that positive views of AI usefulness are linked to academic stress, but other factors such as digital skills or cognitive load did not independently predict stress in this model.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.649[a]	.421	.356	.49511	.421	6.451	7	62	<.001

a. Predictors: (Constant), InstitutionalSupport_Mean, GermaneLoad_Mean, IntrinsicLoad_Mean, DigitalLiteracy_Mean, PEOU_Mean, ExtraneousLoad_Mean, PU_Mean

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11.069	7	1.581	6.451	<.001[b]
	Residual	15.198	62	.245		
	Total	26.268	69			

a. Dependent Variable: AcademicStress_Mean

b. Predictors: (Constant), InstitutionalSupport_Mean, GermaneLoad_Mean, IntrinsicLoad_Mean, DigitalLiteracy_Mean, PEOU_Mean, ExtraneousLoad_Mean, PU_Mean

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.319	.669		.476	.636		
	PU_Mean	.355	.107	.471	3.300	.002	.458	2.182
	PEOU_Mean	.022	.077	.033	.290	.773	.711	1.407
	IntrinsicLoad_Mean	.127	.073	.173	1.725	.089	.928	1.078
	ExtraneousLoad_Mean	.071	.084	.093	.842	.403	.757	1.322
	GermaneLoad_Mean	.123	.080	.203	1.541	.128	.536	1.865
	DigitalLiteracy_Mean	-.032	.079	-.043	-.410	.683	.837	1.195
	InstitutionalSupport_Mean	.087	.059	.154	1.467	.147	.850	1.177

a. Dependent Variable: AcademicStress_Mean

Table 9: Multiple linear regression predicting academic stress from cognitive load, AI perceptions, digital literacy, and institutional factors (N = 70).

4.5 Moderation Analysis

To further explore the conditional nature of the relationship between AI-related perceptions and academic stress, a series of moderation analyses were conducted using the PROCESS macro for SPSS (Model 1). These analyses examined whether the strength or direction of the effect of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) on Academic Stress varied depending on levels of three key moderating variables: Digital Literacy, Ethical Clarity, and Institutional Support.

Each moderator was analyzed separately for both PU and PEOU to identify any statistically significant interaction effects. In cases where the interaction term was significant, simple slopes analyses were conducted at low, average, and high levels of the moderator to interpret the conditional effects.

The results are presented below for each moderator-predictor pair.

4.5.1 PU x Ethical Clarity

A moderation analysis using Model 1 of the PROCESS macro was conducted to determine whether Ethical Clarity moderates the relationship between Perceived Usefulness (PU) of AI tools and Academic Stress. Prior to analysis, all variables were mean-centered to aid interpretation of interaction terms.

The overall model was statistically significant, $F(3, 66) = 13.17$, $p < .001$, explaining 37.4% of the variance in academic stress ($R^2 = .374$). PU had a strong positive effect on academic stress ($\beta = 0.441$, $p < .001$), indicating that students who perceived AI tools as more useful also tended to report higher levels of stress. In contrast, Ethical Clarity itself was not a significant predictor ($\beta = 0.049$, $p = .409$), and the interaction term between PU and Ethical Clarity was also non-significant ($\beta = 0.105$, $p = .222$).

This indicates that Ethical Clarity did not significantly alter the strength or direction of the relationship between PU and stress. That is, students' understanding of ethical boundaries related to AI usage did not buffer or amplify the stress linked to perceived usefulness.

The detailed SPSS output of this moderation analysis, including the interaction plot and coefficients, is presented table 10.

```
OUTCOME VARIABLE:
 Stress

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6119      .3744      .2490    13.1660     3.0000    66.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.3372      .0610    54.7037      .0000     3.2154     3.4590
PU            .4410      .0757     5.8263      .0000      .2899      .5921
Ethical       .0486      .0585      .8304      .4093     -.0682      .1653
Int_1         .1053      .0855     1.2320      .2223     -.0654      .2760

Product terms key:
 Int_1    :        PU       x        Ethical

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0144     1.5177     1.0000    66.0000      .2223
----------
    Focal predict: PU       (X)
          Mod var: Ethical  (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   PU         Ethical    Stress     .
BEGIN DATA.
     -.6993    -1.4571     3.0654
      .2107    -1.4571     3.3271
      .7107    -1.4571     3.4708
     -.6993      .0429     3.0278
      .2107      .0429     3.4332
      .7107      .0429     3.6560
     -.6993     1.0429     3.0027
      .2107     1.0429     3.5040
      .7107     1.0429     3.7794
END DATA.
GRAPH/SCATTERPLOT=
 PU       WITH     Stress   BY       Ethical  .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000
```

Table 10: Moderation Analysis Perceived Usefulness x Ethical Clarity

4.5.2 PU x Institutional Support

A second moderation analysis was conducted to examine whether Institutional Support moderates the relationship between Perceived Usefulness (PU) and Academic Stress, again using PROCESS Model 1. Variables were mean-centered before creating the interaction term.

The model as a whole was statistically significant, $F(3, 66) = 13.17$, $p < .001$, accounting for 37.4% of the variance in academic stress ($R^2 = .374$), identical to the PU × Ethical Clarity model due to the same input structure. PU remained a significant predictor of academic stress ($\beta = 0.441$, $p < .001$), meaning students who found AI tools more useful tended to experience higher stress.

However, Institutional Support was not a significant independent predictor ($\beta = 0.049$, $p = .409$), and its interaction with PU also failed to reach significance ($\beta = 0.105$, $p = .222$). This suggests that students' perceptions of available support and policy guidance did not significantly alter the relationship between perceived usefulness and academic stress.

These findings are detailed in table 11, which shows the coefficients, interaction effect, and the plotted moderation model output from SPSS.

```
OUTCOME VARIABLE:
 Stress

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6119      .3744      .2490    13.1660     3.0000    66.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.3372      .0610    54.7037      .0000     3.2154     3.4590
PU            .4410      .0757     5.8263      .0000      .2899      .5921
ISup_M        .0486      .0585      .8304      .4093     -.0682      .1653
Int_1         .1053      .0855     1.2320      .2223     -.0654      .2760

Product terms key:
 Int_1    :        PU       x        ISup_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0144     1.5177     1.0000    66.0000      .2223
----------
    Focal predict: PU       (X)
          Mod var: ISup_M   (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   PU         ISup_M     Stress     .
BEGIN DATA.
     -.6993    -1.4571     3.0654
      .2107    -1.4571     3.3271
      .7107    -1.4571     3.4708
     -.6993      .0429     3.0278
      .2107      .0429     3.4332
      .7107      .0429     3.6560
     -.6993     1.0429     3.0027
      .2107     1.0429     3.5040
      .7107     1.0429     3.7794
END DATA.
GRAPH/SCATTERPLOT=
 PU       WITH     Stress   BY       ISup_M   .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000
```

Table 11: Moderation Analysis Perceived Usefulness x Institutional Support

4.5.3 PU x Digital Literacy

This moderation analysis examined whether Digital Literacy moderates the relationship between Perceived Usefulness (PU) of AI tools and Academic Stress, using PROCESS Model 1. All variables were mean-centered prior to analysis.

The overall model was statistically significant, $F(3, 66) = 15.88$, $p < .001$, explaining 41.9% of the variance in academic stress ($R^2 = .419$). PU again showed a strong positive relationship with academic stress ($\beta = 0.412$, $p < .001$), reaffirming the pattern observed in previous models.

Most importantly, the interaction between PU and Digital Literacy was significant ($\beta = 0.269$, $p = .005$), indicating a moderation effect. Conditional effects analysis revealed that the effect of PU on academic stress increased with higher levels of digital literacy:

- At low digital literacy, the effect was small and nonsignificant ($\beta = 0.137$, $p = .297$),
- At the average level, the effect was significant ($\beta = 0.406$, $p < .001$),
- And at high digital literacy, the effect was strongest ($\beta = 0.675$, $p < .001$).

This implies that the more digitally literate students are, the more strongly they experience academic stress when they view AI tools as useful, possibly due to greater expectations or reliance.

The full model coefficients, interaction term, and conditional effects are visualized in table 12, providing an overview of how digital literacy influences the stress impact of perceived AI usefulness.

```
OUTCOME VARIABLE:
 Stress

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6475      .4192      .2311    15.8812     3.0000    66.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.2751      .0597    54.8871      .0000     3.1560     3.3943
PU            .4118      .0743     5.5452      .0000      .2635      .5601
DLit_M       -.0129      .0726     -.1774      .8597     -.1578      .1320
Int_1         .2686      .0933     2.8799      .0054      .0824      .4549

Product terms key:
 Int_1    :        PU       x        DLit_M

Test(s) of highest order unconditional interaction(s):
       R2-chng         F        df1        df2          p
X*W      .0730    8.2941     1.0000    66.0000      .0054
----------
    Focal predict: PU       (X)
          Mod var: DLit_M   (W)

Conditional effects of the focal predictor at values of the moderator(s):

     DLit_M     Effect         se          t          p       LLCI       ULCI
    -1.0214      .1374      .1307     1.0516      .2968     -.1235      .3983
     -.0214      .4060      .0746     5.4400      .0000      .2570      .5551
      .9786      .6747      .1071     6.3006      .0000      .4609      .8885

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   PU         DLit_M     Stress     .
BEGIN DATA.
     -.6993    -1.0214     3.1922
      .2107    -1.0214     3.3172
      .7107    -1.0214     3.3859
     -.6993     -.0214     2.9915
      .2107     -.0214     3.3610
      .7107     -.0214     3.5640
     -.6993      .9786     2.7907
      .2107      .9786     3.4047
      .7107      .9786     3.7420
END DATA.
GRAPH/SCATTERPLOT=
 PU       WITH     Stress   BY       DLit_M   .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
```

Table 12: Moderation Analysis Perceived Usefulness x Digital Literacy

4.5.4 PEOU x Ethical Clarity

This analysis tested whether Ethical Clarity moderates the relationship between Perceived Ease of Use (PEOU) of AI tools and Academic Stress, using PROCESS Model 1 with centered variables.

The overall model was not statistically significant, $F(3, 66) = 2.15$, $p = .102$, explaining only 8.9% of the variance in academic stress ($R^2 = .089$). Still, PEOU showed a modest but significant direct effect on academic stress ($\beta = 0.170$, $p = .037$), suggesting that students who find AI tools easier to use may experience a small but statistically significant increase in perceived stress.

However, the interaction between PEOU and Ethical Clarity was not significant ($\beta = 0.117$, $p = .167$), indicating that ethical clarity does not significantly influence the relationship between ease of use and stress levels. The relationship appears consistent across different levels of perceived ethical clarity.

This lack of moderation is visualized in table 13, which displays the flat interaction lines representing the relationship between PEOU and stress across varying levels of ethical clarity.

```
OUTCOME VARIABLE:
 Stress

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2985      .0891      .3625     2.1515     3.0000    66.0000      .1021

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.3132      .0722    45.8842      .0000     3.1690     3.4574
PEOU_M        .1698      .0796     2.1322      .0367      .0108      .3288
Ethical      -.0212      .0685     -.3090      .7583     -.1579      .1156
Int_1         .1168      .0835     1.3990      .1665     -.0499      .2834

Product terms key:
 Int_1    :        PEOU_M   x        Ethical

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0270     1.9571     1.0000    66.0000      .1665
----------
    Focal predict: PEOU_M   (X)
          Mod var: Ethical  (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   PEOU_M     Ethical    Stress     .
BEGIN DATA.
    -1.0643    -1.4571     3.3444
     -.0643    -1.4571     3.3440
      .9357    -1.4571     3.3437
    -1.0643      .0429     3.1262
     -.0643      .0429     3.3010
      .9357      .0429     3.4759
    -1.0643     1.0429     2.9808
     -.0643     1.0429     3.2724
      .9357     1.0429     3.5640
END DATA.
GRAPH/SCATTERPLOT=
 PEOU_M   WITH     Stress   BY       Ethical  .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000
```

Table 13: Moderation Analysis Perceived Ease of Use x Ethical Clarity

4.5.5 PEOU x Institutional Support

To assess whether Institutional Support moderates the relationship between Perceived Ease of Use (PEOU) and Academic Stress, PROCESS Model 1 was applied with mean-centered variables.

The overall model was not statistically significant, $F(3, 66) = 2.15$, $p = .102$, with an explained variance of 8.9% ($R^2 = .089$), mirroring the previous analysis. PEOU again had a small but significant positive association with academic stress ($\beta = 0.170$, $p = .037$), reinforcing the idea that usability alone may not reduce pressure and could potentially enhance expectations.

However, the interaction between PEOU and Institutional Support was not significant ($\beta = 0.117$, $p = .167$), suggesting that the level of perceived support from institutions does not meaningfully alter the effect of PEOU on stress.

This result is illustrated in table 14, where the interaction lines remain largely parallel, showing no substantial change in stress patterns across levels of institutional support.

```
OUTCOME VARIABLE:
 Stress

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2985      .0891      .3625     2.1515     3.0000    66.0000      .1021

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.3132      .0722    45.8842      .0000     3.1690     3.4574
PEOU_M        .1698      .0796     2.1322      .0367      .0108      .3288
ISup_M       -.0212      .0685     -.3090      .7583     -.1579      .1156
Int_1         .1168      .0835     1.3990      .1665     -.0499      .2834

Product terms key:
 Int_1    :        PEOU_M   x        ISup_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0270     1.9571     1.0000    66.0000      .1665
----------
    Focal predict: PEOU_M   (X)
          Mod var: ISup_M   (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   PEOU_M     ISup_M     Stress     .
BEGIN DATA.
    -1.0643    -1.4571     3.3444
     -.0643    -1.4571     3.3440
      .9357    -1.4571     3.3437
    -1.0643      .0429     3.1262
     -.0643      .0429     3.3010
      .9357      .0429     3.4759
    -1.0643     1.0429     2.9808
     -.0643     1.0429     3.2724
      .9357     1.0429     3.5640
END DATA.
GRAPH/SCATTERPLOT=
 PEOU_M   WITH     Stress   BY       ISup_M   .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000
```

Table 14: Moderation Analysis Perceived Ease of Use x Institutional Support

4.5.6 PEOU x Digital Literacy

This moderation analysis tested whether Digital Literacy moderates the relationship between Perceived Ease of Use (PEOU) and Academic Stress using PROCESS Model 1 with mean-centered variables.

The overall model was statistically significant, $F(3, 66) = 3.18$, $p = .030$, accounting for 12.6% of the variance in academic stress ($R^2 = .126$). PEOU was positively associated with academic stress ($\beta = 0.172$, $p = .043$), indicating that students who found AI tools easier to use also reported slightly higher stress levels, possibly due to heightened expectations or more frequent engagement with academic tasks.

Importantly, the interaction between PEOU and Digital Literacy was statistically significant ($\beta = 0.181$, $p = .032$), revealing that digital literacy influenced how ease of use related to stress. Simple slopes analysis showed that at low levels of digital literacy, PEOU had no significant effect on stress ($p = .910$), whereas at average and high levels, PEOU significantly increased stress ($p = .048$ and $p = .005$, respectively).

As shown in table 15, the interaction plot illustrates a steeper positive slope for students with high digital literacy, suggesting that greater digital skills may amplify the psychological impact of using easily accessible AI tools.

```
OUTCOME VARIABLE:
 Stress

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3554      .1263      .3477     3.1813     3.0000    66.0000      .0296

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.2731      .0739    44.3162      .0000     3.1257     3.4206
PEOU_M        .1721      .0835     2.0617      .0432      .0054      .3388
DLit_M        .0762      .0949      .8030      .4248     -.1133      .2657
Int_1         .1813      .0829     2.1876      .0322      .0158      .3467

Product terms key:
 Int_1    :        PEOU_M   x        DLit_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0633     4.7855     1.0000    66.0000      .0322
----------
    Focal predict: PEOU_M   (X)
          Mod var: DLit_M   (W)

Conditional effects of the focal predictor at values of the moderator(s):

     DLit_M     Effect         se          t          p       LLCI       ULCI
    -1.0214     -.0130      .1151     -.1134      .9100     -.2428      .2167
     -.0214      .1682      .0834     2.0175      .0477      .0017      .3347
      .9786      .3495      .1200     2.9123      .0049      .1099      .5891

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   PEOU_M     DLit_M     Stress     .
BEGIN DATA.
    -1.0643    -1.0214     3.2091
     -.0643    -1.0214     3.1961
      .9357    -1.0214     3.1830
    -1.0643     -.0214     3.0924
     -.0643     -.0214     3.2607
      .9357     -.0214     3.4289
    -1.0643      .9786     2.9757
     -.0643      .9786     3.3252
      .9357      .9786     3.6748
END DATA.
GRAPH/SCATTERPLOT=
 PEOU_M   WITH     Stress   BY       DLit_M   .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
```

Table 15: Moderation Analysis Perceived Ease of Use x Digital Literac

4.6 Serial Mediation Analysis

To better understand the mechanisms through which students' perceptions of AI tools influence academic stress, two serial mediation models were tested using PROCESS Model 6. These models examined whether AI Tool Use and Cognitive Load serve as mediators in the relationship between Perceived Usefulness (PU) and academic stress, and Perceived Ease of Use (PEOU) and academic stress.

Each model follows a path from the predictor (PU or PEOU), through the two mediators (AI Tool Use and Cognitive Load), to the outcome variable (Academic Stress).

4.6.1 Serial Mediation Model for Perceived Usefulness (PU)

A serial mediation analysis was conducted to investigate whether the relationship between Perceived Usefulness (PU) and academic stress was mediated by AI Tool Use and Cognitive Load in sequence (see table 16).

The first regression model showed that PU was a strong predictor of AI Tool Use ($\beta = 1.166$, $p < .001$), indicating that students who found AI tools more useful reported higher levels of actual use.

In the second model, Cognitive Load was regressed on both PU and AI Tool Use. PU had a positive but non-significant effect ($\beta = 0.183$, $p = .112$), while AI Tool Use also did not significantly predict Cognitive Load ($\beta = 0.055$, $p = .481$).

In the final model predicting academic stress, PU significantly predicted stress ($\beta = 0.382$, $p = .003$), and Cognitive Load also showed a significant positive association ($\beta = 0.285$, $p = .032$). However, AI Tool Use did not significantly predict stress in this model ($\beta = -0.009$, $p = .915$).

Bootstrapping analyses (5,000 samples) indicated that:

- The total indirect effect of PU on academic stress was small and not statistically significant (effect = 0.060, 95% CI [-0.178, 0.301]).
- The indirect effect through AI Tool Use only was not significant (effect = -0.010, 95% CI [-0.238, 0.249]).
- The effect through Cognitive Load only was also non-significant (effect = 0.052, 95% CI [-0.030, 0.162]).
- The full serial pathway through both AI Tool Use and Cognitive Load did not reach significance (effect = 0.018, 95% CI [-0.038, 0.106]).

These results suggest that the relationship between perceived usefulness and academic stress is predominantly direct, with little support for mediation through either AI Tool Use or Cognitive Load in this model. Table 16 provides a visual summary of these results.

Model 6 – Serial Mediation PU

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 6
    Y  : Stress
    X  : PU
   M1  : AITU_M
   M2  : CLOAD_M

Sample
Size:  70

**************************************************************************
OUTCOME VARIABLE:
 AITU_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .8014      .6423      .5156   122.0769     1.0000    68.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant    -1.5822      .5125    -3.0875      .0029    -2.6048     -.5596
PU           1.1656      .1055    11.0488      .0000      .9551     1.3761

**************************************************************************
OUTCOME VARIABLE:
 CLOAD_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4129      .1705      .2146     6.8866     2.0000    67.0000      .0019

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.2581      .3531     6.3955      .0000     1.5534     2.9628
PU            .1834      .1138     1.6112      .1118     -.0438      .4105
AITU_M        .0554      .0782      .7085      .4811     -.1007      .2116

**************************************************************************
```

```
**************************************************************************
OUTCOME VARIABLE:
 Stress

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6242      .3896      .2429    14.0437     3.0000    66.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .5700      .4767     1.1957      .2361     -.3818     1.5217
PU            .3820      .1234     3.0957      .0029      .1356      .6283
AITU_M       -.0089      .0836     -.1069      .9152     -.1757      .1579
CLOAD_M       .2852      .1300     2.1947      .0317      .0257      .5447


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .3820      .1234     3.0957      .0029      .1356      .6283

Indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
TOTAL       .0603      .1231     -.1778      .3012
Ind1       -.0104      .1242     -.2379      .2492
Ind2        .0523      .0491     -.0298      .1615
Ind3        .0184      .0355     -.0380      .1060

Indirect effect key:
Ind1  PU          ->    AITU_M      ->    Stress
Ind2  PU          ->    CLOAD_M     ->    Stress
Ind3  PU          ->    AITU_M      ->    CLOAD_M     ->    Stress

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

Table 16: Serial Mediation Analysis Perceived Usefulness

4.6.2 Serial Mediation Model for Perceived Ease of Use (PEOU)

To examine whether the relationship between Perceived Ease of Use (PEOU) and academic stress was mediated sequentially through AI Tool Use and Cognitive Load, a serial mediation analysis (PROCESS Model 6) was conducted (see table 17).

The first regression model indicated that PEOU significantly predicted AI Tool Use (β = 0.522, $p < .001$), suggesting that students who found AI tools easier to use were more likely to use them.

In the second stage, AI Tool Use significantly predicted Cognitive Load (β = 0.187, p = .001), whereas the direct effect of PEOU on Cognitive Load was non-significant (β = -0.099, p = .144), indicating that the influence of ease of use on mental effort may be mediated.

The third regression model, predicting academic stress, revealed that Cognitive Load (β = 0.391, p = .006) and AI Tool Use (β = 0.159, p = .014) were both significant predictors. However, the direct effect of PEOU on stress was not significant (β = 0.086, p = .264), suggesting full mediation.

Bootstrapping analysis (5,000 samples) showed that the total indirect effect of PEOU on academic stress was positive but not statistically significant (effect = 0.082, 95% CI [-0.044, 0.227]). Among the individual indirect pathways:

- The path through AI Tool Use only was significant (effect = 0.083, 95% CI [0.006, 0.186]).
- The path through Cognitive Load only was not significant (effect = -0.039, 95% CI [-0.109, 0.024]).
- The full serial path (PEOU → AI Tool Use → Cognitive Load → Stress) approached significance (effect = 0.038, 95% CI [-0.0001, 0.093]).

These findings suggest that while PEOU does not directly influence academic stress, it may indirectly do so through its positive impact on AI tool use, which in turn influences cognitive load and ultimately stress. Table 17 displays the PROCESS Model 6 output supporting these pathways.

Model 6 – Serial Mediation PEOU

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 6
    Y  : Stress
    X  : PEOU_M
   M1  : AITU_M
   M2  : CLOAD_M

Sample
Size:  70

**************************************************************************
OUTCOME VARIABLE:
 AITU_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3998      .1598     1.2108    12.9355     1.0000    68.0000      .0006

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.8781      .6045     3.1070      .0028      .6719     3.0843
PEOU_M        .5221      .1452     3.5966      .0006      .2324      .8118

**************************************************************************
OUTCOME VARIABLE:
 CLOAD_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4070      .1656      .2159     6.6505     2.0000    67.0000      .0023

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.0131      .2728    11.0465      .0000     2.4686     3.5575
PEOU_M       -.0989      .0669    -1.4796      .1437     -.2324      .0345
AITU_M        .1868      .0512     3.6470      .0005      .0845      .2890

..........................................................................
```

```
**************************************************************************
OUTCOME VARIABLE:
 Stress

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5605      .3142      .2729    10.0798     3.0000    66.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.0252      .5151     1.9903      .0507     -.0032     2.0537
PEOU_M        .0861      .0764     1.1274      .2637     -.0664      .2387
AITU_M        .1587      .0630     2.5179      .0142      .0329      .2846
CLOAD_M       .3905      .1374     2.8428      .0059      .1162      .6647


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .0861      .0764     1.1274      .2637     -.0664      .2387

Indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
TOTAL        .0823      .0682     -.0438      .2268
Ind1         .0829      .0463      .0061      .1856
Ind2        -.0386      .0331     -.1094      .0235
Ind3         .0381      .0250     -.0001      .0931

Indirect effect key:
Ind1  PEOU_M      ->    AITU_M      ->    Stress
Ind2  PEOU_M      ->    CLOAD_M     ->    Stress
Ind3  PEOU_M      ->    AITU_M      ->    CLOAD_M     ->    Stress

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
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Table 17: Serial Mediation Analysis Perceived Ease of Use

4.6.3 Moderation Hypotheses

The moderation analyses tested hypotheses H5 through H7 by evaluating whether digital literacy, ethical clarity, and institutional support moderated the relationship between AI-related perceptions (PU and PEOU) and academic stress.

H5: Ethical Clarity moderates the relationship between AI perceptions and academic stress.
The interaction terms involving ethical clarity were not statistically significant for either PU ($\beta = 0.105$, $p = .222$) or PEOU ($\beta = 0.117$, $p = .167$). These results do not support H5, indicating that students' perceived clarity regarding ethical use of AI did not significantly influence how AI perceptions affected their stress levels.

H6: Institutional Support moderates the relationship between AI perceptions and academic stress.
Similar to H5, no significant interaction effects were found for institutional support with either PU ($\beta = 0.105$, $p = .222$) or PEOU ($\beta = 0.117$, $p = .167$). Thus, H6 is not supported, suggesting that institutional policies or perceived support did not change the stress impact of perceived usefulness or ease of use.

H7: Digital Literacy moderates the relationship between AI perceptions and academic stress.
Significant interaction effects were observed for both PU x Digital Literacy ($\beta = 0.269$, $p = .005$) and PEOU x Digital Literacy ($\beta = 0.181$, $p = .032$). These findings support H7, indicating that digital literacy strengthens the relationship between AI tool perceptions and academic stress. In other words, students with higher digital skills reported greater stress when they viewed AI tools as useful or easy to use.

5 Discussion and Interpretation

This chapter discusses the meaning of the research results in relation to the central research question: To what extent do AI tools influence academic well-being and cognitive workload among Dutch university students? Based on the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT), the study used a quantitative approach to assess how AI tools affect perceived stress, mental effort, and institutional factors. The chapter is organized into five parts: interpretation of results, theoretical contributions, practical implications, study limitations, and suggestions for future research.

5.1 Interpretation of Results

5.1.1 Academic Well-Being and Emotional Responses

The first sub-question examined how AI tools influence students' academic well-being, particularly in terms of stress and emotional responses. The regression analysis showed that Perceived Usefulness (PU) of AI tools was a significant positive predictor of academic stress ($B = 0.441$, $p < .001$), and this was also reflected in a strong positive correlation in the Pearson matrix. These findings suggest a paradox: students who view AI tools as helpful and effective may actually experience more academic stress, not less.

This counterintuitive result invites further interpretation. One possible explanation is that greater perceived usefulness of AI tools increases students' expectations of their own performance. If students believe these tools give them an advantage, they may feel pressured to produce better results, leading to performance anxiety or fear of underachievement. This pattern is consistent with findings in technostress literature, where highly valued digital tools can lead to increased pressure, especially when users feel they must fully leverage those tools to keep up academically (Tarafdar et al., 2011; Ayyagari et al., 2011).

Another plausible mechanism is that AI tools normalize higher productivity standards. As students observe their peers using AI to generate, summarize, or correct academic texts quickly, those who also perceive these tools as effective may feel compelled to match this accelerated pace, leading to heightened cognitive and emotional demands. In this sense, AI's perceived usefulness may unintentionally drive a culture of academic overperformance, especially in competitive disciplines such as Business and Computer Science, which were overrepresented in the sample.

Interestingly, Perceived Ease of Use (PEOU) was not a significant predictor of academic stress in the regression model, although it showed a modest positive correlation. This challenges the Technology Acceptance Model (TAM), which posits that ease of use should lead to more favorable outcomes. One possible reason is that while usability may enhance adoption, it does not directly alleviate the emotional pressure associated with academic performance. In fact, students with high digital literacy and comfort with

AI tools may engage with them more intensely, as seen in the moderation analysis, which showed stronger PU–stress effects at higher levels of digital literacy.

Overall, these findings indicate that AI tools are not neutral learning aids. Their perceived usefulness can amplify emotional stakes in academic settings, suggesting that psychological responses such as stress are shaped not only by what tools can do, but by what students feel they must achieve using them.

5.1.2 Cognitive Load and Academic Autonomy

The second sub-question examined how AI tools affect students' cognitive workload and perceptions of academic autonomy. Although descriptive results showed moderate levels of intrinsic and extraneous cognitive load, the multiple regression analysis revealed that none of the cognitive load components significantly predicted academic stress when perceived usefulness (PU) and perceived ease of use (PEOU) were included as predictors. This calls for closer interpretation of why cognitive load, a key construct in Cognitive Load Theory (CLT), appeared statistically weak in the context of this study.

One possible explanation lies in the overlap between cognitive load variables and PU. Students who perceive AI tools as highly useful may also be more likely to report engagement in germane cognitive processes, efforts that are mentally demanding but positively associated with learning. Since PU showed a strong positive association with germane load and was also the only significant predictor of academic stress, it is plausible that variance typically attributed to cognitive effort may have been subsumed under PU in this analysis. This supports the idea of overlap between variables, where similar predictors can reduce each other's impact in a regression model (Field, 2018).

Another possible reason why cognitive load was not significant may be the homogeneity of the sample. The participants were mostly university students who are likely accustomed to managing high academic workloads and navigating digital learning environments. As such, their cognitive effort in using AI tools may not have been perceived as burdensome or out of the ordinary. In such populations, variance in cognitive load may be too low to detect robust effects, particularly in a sample of 70 participants.

Moreover, it is also possible that the cognitive load items, though adapted from validated scales, did not fully capture the nuanced ways in which AI tools impact students' mental effort. For instance, the distinction between intrinsic and extraneous load may not be intuitively clear to respondents, especially when they evaluate a tool like ChatGPT that simultaneously reduces information-seeking effort but may add uncertainty or ambiguity in academic judgment. Prior research has shown that measurement precision is crucial in detecting subtle relationships within CLT frameworks (Leppink et al., 2013).

Taken together, these findings suggest that while cognitive load remains a theoretically relevant factor, its statistical influence may be masked by more salient constructs like perceived usefulness or limited by methodological constraints in this study. Future studies should explore these relationships using more refined instruments and potentially mixed-method approaches to better capture how students experience mental effort in AI-supported academic contexts.

5.1.3 Ethical and Practical Concerns Regarding AI Tools

The third sub-question focused on how ethical clarity and institutional support shape students' attitudes and behaviors toward AI tools. Descriptive statistics revealed that students perceived moderate levels of ethical clarity and institutional support, with both variables showing relatively low mean scores ($M = 2.96$), indicating some uncertainty or lack of formal guidance. However, moderation analyses using the PROCESS macro showed that neither ethical clarity nor institutional support significantly moderated the relationship between perceived usefulness (PU) and academic stress. This suggests that these institutional factors did not change how students experienced stress in relation to how useful they perceived AI tools to be.

While the data shows that ethical clarity does not directly reduce academic stress, this finding should not be interpreted as evidence that ethical policies are irrelevant. Instead, it may reflect the broader institutional reality: Dutch universities may not yet formally promote or regulate AI tools in academic settings. Without clear, enforced policies, students may rely on informal norms or guesswork, leading to uncertainty and uneven practices. This could explain why ethical clarity lacked a moderating effect, because such clarity is not sufficiently established or internalized among the student body.

These findings align with previous literature. For example, Eaton, Pethrick, and Turner (2023) emphasized that vague or inconsistently communicated academic integrity policies can cause confusion and harm students' mental well-being. Similarly, Davis (2022) found that unclear academic procedures can heighten anxiety, particularly for students from diverse or disadvantaged backgrounds. In such cases, institutional ambiguity, not just individual perceptions, can drive stress.

Thus, the absence of a significant moderation effect may not signal that ethical guidance is unimportant, but rather that it is currently underdeveloped or inconsistently experienced. Until policies are well-communicated, enforced, and supported with practical tools and training, their impact on student well-being may remain limited.

The findings suggest that ethical and institutional clarity alone are insufficient to influence students' stress levels, but this may be because such structures are not yet effectively integrated into students' academic environments.

6 Conclusion

This chapter provides a conclusive overview of the research, guided by the main research question: *To what extent do AI tools influence academic well-being and cognitive workload among university students in the Netherlands?* This chapter answers the sub-questions and main research question. The final sections outline the theoretical and practical contributions, study limitations, directions for future research, and implications for educational practice.

Answer to Research Questions

This study used a quantitative, cross-sectional design to explore how AI tools like ChatGPT and Grammarly impact students' academic stress, cognitive workload, and ethical concerns. The study was grounded in the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT), and drew on responses from 70 university students across various disciplines in the Netherlands.

Sub-question 1: How do AI tools affect students' academic well-being, including perceived stress and emotional response to academic tasks?

A key finding was that perceived usefulness (PU) of AI tools is positively and significantly associated with academic stress. Students who found AI tools helpful reported higher stress levels, suggesting that increased expectations, self-imposed pressure, or fear of falling behind may accompany the perceived benefits. This aligns with the idea of a performance-pressure paradox: when tools are seen as indispensable for success, they may create a new layer of academic strain.

In contrast, perceived ease of use (PEOU) had a weaker and inconsistent relationship with stress, indicating that usability alone is not sufficient to mitigate emotional strain. These findings challenge TAM's assumption that usability always enhances user satisfaction and suggest emotional and motivational factors must be integrated into adoption models.

Sub-question 2: To what extent do AI tools influence cognitive workload and academic autonomy in learning tasks?

Correlation analysis showed positive associations between academic stress and both intrinsic and germane load, suggesting that students engage in deep learning but also face high task complexity. However, none of the cognitive load dimensions were significant predictors in the regression model. One possible explanation is overlapping variance between cognitive load and PU, as students who find AI tools useful may also take on more complex tasks, which increases both load and stress. Another possibility is measurement sensitivity: the cognitive load items may not have captured nuanced differences in workload perceptions, especially within a relatively homogeneous sample of university students.

Sub-question 3: What ethical and practical concerns do students have about AI tools, and how do these concerns affect their attitudes and academic behavior?

Students reported moderate levels of ethical clarity and institutional support, indicating some awareness of academic integrity policies. However, neither ethical clarity nor institutional support significantly predicted stress, and no moderating effects were found. While these results suggest ethical concerns do not directly affect well-being, students' open-ended responses reflected uncertainty and a desire for clearer guidance. This points to a practical gap: even if ethical clarity doesn't directly reduce stress, its absence may contribute to confusion, insecurity, or inconsistent usage practices.

Main Research Question: *To what extent do AI tools influence academic well-being and cognitive workload among university students in the Netherlands?*

The influence of AI tools on academic well-being is shaped more by students' perceptions of usefulness than by cognitive or institutional factors. While AI tools can support learning, they also appear to amplify performance-related stress when students rely heavily on them. The findings highlight the psychological and emotional trade-offs that come with adopting AI in education, underscoring the need to pair technological innovation with appropriate student support and policy guidance.

Conclusion

This research examined how AI tools influence academic well-being and cognitive workload among university students in the Netherlands, using the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT) as theoretical frameworks. Through a quantitative, cross-sectional survey of 70 students across diverse academic fields, the study investigated how perceptions of AI usefulness, usability, and institutional support relate to academic stress and mental effort.

The most prominent finding was the positive association between perceived usefulness (PU) of AI tools and academic stress, revealing a paradox. Tools designed to support students may simultaneously intensify performance pressure. This challenges a core assumption of TAM, namely that greater perceived usefulness leads to better outcomes, and highlights the importance of understanding not just whether students adopt AI, but how they experience its impact emotionally.

Cognitive load dimensions, particularly intrinsic and germane load, were associated with stress at a correlational level, but did not predict stress in multivariate models, possibly due to shared variance with PU or limited variation in the sample. CLT thus played a supporting role, offering insight into students' mental engagement with academic tasks, but proving secondary to motivational factors like perceived utility.

Although ethical clarity and institutional support were not statistically significant predictors or moderators, their importance emerged in students' expressed desire for clearer guidelines and academic policies. This suggests that even if institutional factors do not directly affect stress, they form a necessary foundation for responsible and confident AI use.

6.1 Contribution

Theoretical Contributions

This study makes several theoretical contributions by refining the understanding of how AI tools interact with academic well-being and cognitive workload, particularly within the frameworks of the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT). Traditionally, TAM suggests that higher perceived usefulness of a tool leads to more favorable outcomes, including acceptance and satisfaction. However, the current findings introduce a paradox: perceived usefulness was positively associated with academic stress. This suggests that students who consider AI tools beneficial may simultaneously feel pressured to meet higher standards, likely due to elevated expectations or fear of falling behind. These results challenge the assumption that usefulness always translates to positive academic or emotional outcomes and indicate a need to expand TAM by integrating emotional and motivational components that account for psychological strain.

The study also extends CLT by exploring how cognitive load interacts with student well-being in AI-supported academic environments. Although intrinsic and germane load were positively correlated with academic stress, none of the cognitive load variables significantly predicted stress when included in multivariate analyses alongside perceived usefulness. This outcome indicates that emotional and perceptual variables, such as tool usefulness, may be more central to understanding student stress than task complexity alone. As such, cognitive load theory might benefit from incorporating contextual and emotional moderators, particularly in digital learning settings where performance expectations are shaped not only by content but also by perceptions of technology.

In addition, this study sheds light on the limited but nuanced role of ethical clarity. Although ethical clarity did not significantly moderate the relationship between perceived usefulness and stress, students still reported a need for clearer institutional policies and guidelines. This suggests that policy transparency alone may not be enough to impact student well-being, but it may still serve as a foundation for building trust and reducing uncertainty. Future theoretical models in educational technology should therefore consider not only the existence of policies but also how they are communicated and perceived by students.

Practical Contributions

On a practical level, the findings highlight that student perceptions of AI tools exert significant influence even in the absence of formal institutional promotion. Although

Dutch universities have not yet fully integrated AI tools into their official educational strategies, students are independently adopting them in meaningful ways. This bottom-up usage implies that institutions must address the emotional and academic implications of AI, regardless of whether they formally endorse these tools. Failure to do so may leave students navigating complex technological and ethical decisions without adequate support.

Moreover, while ethical clarity and institutional support did not emerge as strong predictors of academic stress in the data, students' feedback reveals a persistent desire for structured guidance. This highlights a mismatch between student needs and current university practices. As such, universities should not wait for widespread AI integration before developing ethical frameworks, training programs, and digital literacy initiatives. Proactive engagement in these areas can prepare students to use AI responsibly and with greater confidence.

Finally, the study suggests that effective AI integration must go beyond promoting tool efficiency. Institutions and developers alike must consider how AI tools influence students' emotional states, expectations, and sense of control. Supporting student well-being should be viewed as a core element of AI adoption in education, not a secondary concern. This requires designing learning environments that pair technological innovation with psychological and ethical support systems.

6.2 Limitations

While this study offers valuable insights into how AI tools affect academic well-being and cognitive workload, several limitations must be acknowledged to contextualize the findings.

First, the sample size was modest, with 70 students participating. Although sufficient for initial exploratory and regression analyses, this limits the generalizability of the results. A larger and more diverse sample would have strengthened statistical power and allowed for subgroup comparisons, such as differences across disciplines, educational levels, or institutional types.

Second, the study relied on self-reported survey data. This method introduces potential biases such as social desirability bias and recall bias. For example, students may have over- or under-reported their use of AI tools or their levels of academic stress based on perceived expectations or memory limitations. These factors may influence the accuracy of key measures like perceived usefulness, cognitive load, and stress.

Third, the cross-sectional design prevents any conclusions about causality. While associations between variables like perceived usefulness and academic stress were statistically significant, the direction of influence cannot be definitively established. It is possible that students already experiencing stress may perceive AI tools as more necessary or useful, rather than AI use causing stress. Longitudinal designs are needed to clarify temporal and causal relationships.

Fourth, the study did not directly examine how institutional policies or curricula integrate AI tools. Although students reported on ethical clarity and institutional support, the research did not verify whether Dutch universities formally promote AI adoption. This makes it difficult to draw definitive conclusions about institutional effects, and it limits the scope of practical recommendations related to policy change.

Finally, the measures used to assess constructs like cognitive load and digital literacy, while grounded in prior literature, may not have fully captured the complexity of students' academic and emotional experiences. The moderate internal consistency of the overall survey (Cronbach's $\alpha = 0.694$) suggests room for improvement in instrument design or construct coverage in future studies.

6.3 Future Research Directions

Building on the findings and limitations of this study, several avenues for future research can deepen understanding of the complex relationship between AI tools, academic well-being, and cognitive workload.

First, future studies should use larger and more diverse samples. Including students from multiple universities, programs, and demographic groups such as undergraduate compared to postgraduate levels or technical compared to non-technical disciplines would enhance the generalizability of findings and allow for subgroup comparisons. Diversity in sampling can also shed light on whether certain populations are more vulnerable to AI-related academic stress.

Second, a longitudinal research design would help clarify the directionality of observed relationships. For example, tracking students' AI usage and stress levels over time could reveal whether AI tools lead to increased academic pressure or whether students under greater stress seek out AI tools as coping mechanisms. Longitudinal studies would also allow for the examination of changes in attitudes and behaviors as AI adoption becomes more widespread.

Third, future research should integrate mixed methods approaches. While quantitative surveys provide valuable statistical insights, qualitative data from interviews or focus groups could capture the emotional nuances, ethical dilemmas, and contextual experiences that structured instruments may overlook. These insights could illuminate how students interpret institutional policies, perceive AI-generated content, or experience performance pressure when using these tools.

Fourth, experimental studies can be useful to evaluate the effectiveness of targeted interventions. For instance, researchers could test the impact of digital literacy workshops, AI usage guidelines, or stress management programs on students' well-being and academic performance. Such interventions could clarify whether institutions can mitigate stress by providing better support around AI usage.

Finally, future studies should further investigate moderating variables that may shape the relationship between AI perceptions and academic stress. These could include factors like emotional intelligence, academic resilience, students' perceptions of institutional trust, or the presence of peer norms regarding AI tool use. Identifying such moderators can help explain why some students benefit from AI tools while others experience increased pressure.

6.4 Practical Implications

The findings of this study suggest that AI tools, although perceived as useful, may unintentionally contribute to elevated academic stress. These insights offer several cautious and context-sensitive implications for practice, especially for educational stakeholders seeking to integrate AI tools in supportive and responsible ways.

First, institutions should be mindful of the psychological pressures that may accompany the perceived usefulness of AI tools. When students view these technologies as essential for academic success, this can raise performance expectations and exacerbate stress. Rather than promoting AI tools as universally beneficial, universities should foster balanced messaging that includes both the strengths and limitations of these tools. This helps set realistic expectations and prevents the emergence of pressure-based norms around AI usage.

Second, while the study did not provide evidence that Dutch universities formally endorse AI tools, students' feedback reflected a need for clearer ethical and institutional guidance. Therefore, rather than recommending broad institutional reforms, the practical suggestion is to open a dialogue with students. This can involve co-creating guidelines or clarifying acceptable practices in collaboration with academic communities. Even though ethical clarity did not significantly reduce stress in this study, the presence of ambiguous policies can still create confusion or uncertainty that undermines student confidence.

Third, the findings imply that digital literacy may play a complex role in shaping how students experience academic stress when using AI tools. While high digital literacy was linked to greater stress under high perceived usefulness, it also signals that digitally competent students are more engaged and potentially more dependent on AI tools. As such, institutions should frame digital literacy not just as a technical skill but as part of a broader digital well-being strategy. Programs that combine digital skills training with stress management and critical thinking could help students navigate AI use more sustainably.

Finally, any implementation of AI tools in academic contexts should be accompanied by ongoing research and evaluation. Given the rapid evolution of these technologies and the complexity of student responses, universities should adopt flexible and adaptive approaches to AI integration, informed by regular feedback and updated evidence. Institutions should not assume that what benefits one group of students will apply to all, or that usefulness translates directly into well-being.

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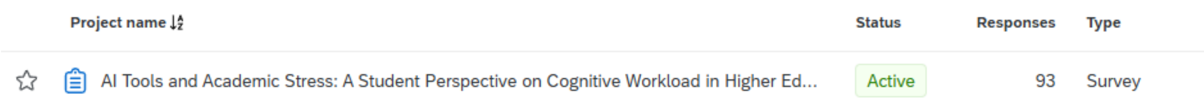
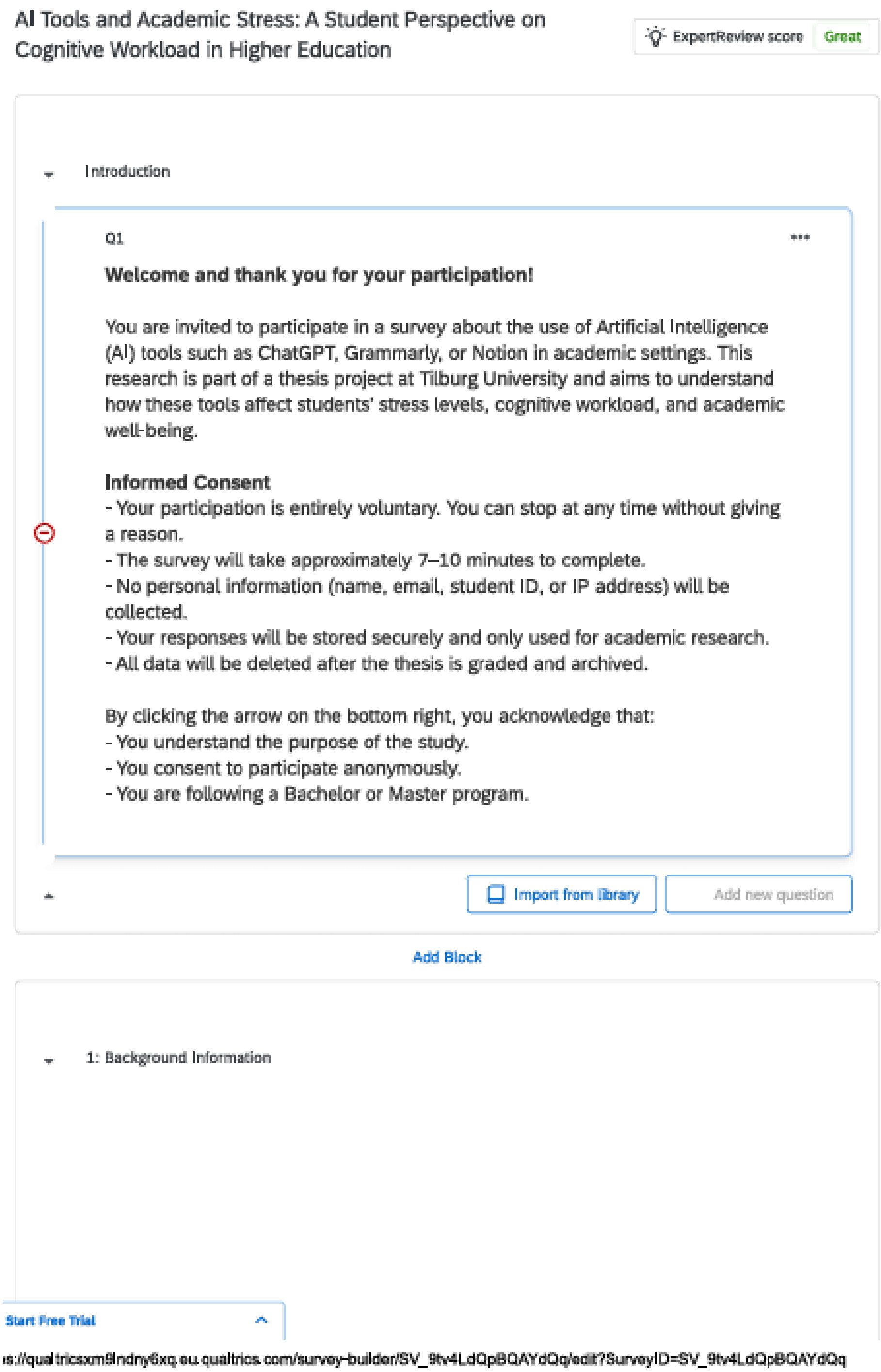
8 Appendix.

8.1 Survey Responses



8.2 Survey Qualtrics



Q2

What is your age

- Under 18
- 18 - 24
- 25 - 34
- 35 - 44
- 45 - 54
- 55 - 64
- 65 - 74
- 75 - 84
- 85 or older

Import from library | Add new question

Add Block

1: Background Information

Q3

What is your gender

- Male
- Female
- Non-binary / third gender
- Prefer not to say

Import from library | Add new question

Add Block

1: Background Information

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Q4

Field of study

- Business / Economics / Management
- Law
- Social Sciences
- Humanities
- Engineering
- Computer Science
- Natural Sciences
- Medicine / Health Services
- Education
- Communication
- Environmental Studies
- Mathematics
- Arts / Design / Architecture
- Public Administration / Policy Studies
- Tourism / Hospitality

Import from library | Add new question

Add Block

2: AI Usage and Perceptions: Perceived Usefulness

Q5

AI tools improve my academic performance.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library | Add new question

Add Block

2: AI Usage and Perceptions: Perceived Usefulness

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Q6

AI tools help me complete academic tasks more efficiently.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library | Add new question

Add Block

2: AI Usage and Perceptions: Perceived Usefulness

Q7

AI tools support my understanding of academic content.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library | Add new question

Add Block

2: AI Usage and Perceptions: Perceived Usefulness

Q8

AI tools help me save time when studying.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

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Import from library Add new question

Add Block

2: AI Usage and Perceptions: Perceived Ease of Use

Q9

I find AI tools easy to use.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library Add new question

Add Block

2: AI Usage and Perceptions: Perceived Ease of Use

Q10

Learning to use AI tools is straightforward for me.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library Add new question

Add Block

2: AI Usage and Perceptions: Behavioral Intention & Usage

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Q11

I intend to continue using AI tools for academic work.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library | Add new question

Add Block

2: AI Usage and Perceptions: Behavioral Intention & Usage

Q12

I frequently use AI tools for academic tasks.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library | Add new question

Add Block

3: Cognitive Load: Intrinsic Load

Q13

Academic tasks are mentally demanding even with AI tools.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

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Import from library | Add new question

Add Block

3: Cognitive Load: Intrinsic Load

Q14 *

I still find course content difficult to understand even when using AI tools.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library | Add new question

Add Block

3: Cognitive Load: Extraneous Load

Q15 *

Using AI tools sometimes makes academic tasks more confusing.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library | Add new question

Add Block

3: Cognitive Load: Extraneous Load

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Q16

Poorly designed AI interfaces distract me from focusing on the task.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library | Add new question

Add Block

3: Cognitive Load: Extraneous Load

Q17

A lack of clear institutional rules about AI usage increases my academic stress.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library | Add new question

Add Block

3: Cognitive Load: Germane Load

Q18

AI tools help me focus on meaningful learning rather than busywork.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

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Import from library | Add new question

Add Block

3: Cognitive Load: Germane Load

Q19

I use AI tools to improve how I approach learning tasks.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library | Add new question

Add Block

4: Academic Stress & Well-being

Q20

I feel overwhelmed by my academic workload

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library | Add new question

Add Block

4: Academic Stress & Well-being

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Q21

I feel anxious about using AI tools for academic work.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library
Add new question

Add Block

4: Academic Stress & Well-being

Q22

AI tools help reduce my academic stress.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library
Add new question

Add Block

4: Academic Stress & Well-being

Q23

Using AI tools makes me feel more in control of my academic responsibilities.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

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Import from library Add new question

Add Block

5: Digital Literacy, Ethics, Institutional Support

Q24 *

I feel confident using digital tools for academic purposes.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library Add new question

Add Block

5: Digital Literacy, Ethics, Institutional Support

Q25 *

I know how to judge the credibility of AI-generated information.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library Add new question

Add Block

5: Digital Literacy, Ethics, Institutional Support

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Q31

My university provides clear policies about the acceptable use of AI tools.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library | Add new question

Add Block

5: Digital Literacy, Ethics, Institutional Support

Q32

My teachers or lecturers have addressed AI tool usage and policies in class.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library | Add new question

Add Block

6: Final Reflections

Q33

I have a clear opinion about the impact of AI tools on student life and education.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

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Import from library Add new question

Add Block

5: Digital Literacy, Ethics, Institutional Support

Q30

I understand when using AI tools is considered academic misconduct.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library Add new question

Add Block

5: Digital Literacy, Ethics, Institutional Support

Q28

I feel unsure about the ethical limits of AI use in academic tasks.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Import from library Add new question

Add Block

End of Survey

We thank you for your time spent taking this survey.

Here is your Mechanical Turk

Code: ${e://Field/RandomSurveyID}

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