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Rulebook vs. Reality

The Influence of University AI
Policies on Student AI Aversion, Attitudes, and Expected
Learning Outcomes

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Rulebook vs. Reality: The Influence of University AI Policies on Student AI Aversion, Attitudes, and Expected Learning Outcomes

by

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ABSTRACT

This study investigates students' general attitudes toward AI and the impact of university AI policies on their attitudes, algorithm aversion, and expected learning outcomes. Utilizing a mixed-methods approach, we conducted document analyses of AI policies from Dutch universities and a scenario-based survey experiment with students. The results of our exploratory analysis revealed that students are highly familiar with AI tools and generally hold positive views regarding the future of AI, although concerns about potential biases persist. The findings from our empirical research indicate that while policies do not directly influence students' trust in AI, restrictive policies prohibiting AI usage lead to a slight change in attitudes. Notably, policies significantly influence the use of AI, with students utilizing AI most frequently in the absence of specific policies. These findings underscore the importance of well-crafted AI policies that promote transparency, fairness, and ethical use to maximize educational benefits. Future research should explore diverse factors and conduct longitudinal studies to further elucidate the long-term effects of AI policy integration. This study contributes to the ongoing discourse on AI in education by highlighting the critical role of policy in shaping students' engagement and learning outcomes with AI technologies.

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Chapter 1

Introduction

For decades, Artificial Intelligence (AI) has been a prominent topic of discussion and debate within society. AI, often portrayed in science fiction as a force that could one day dominate humanity, has been a subject of both fascination and fear These dramatic depictions, however, are more fantasy than reality. In fact, AI is already here, integrated into our day-to-day lives. Its arrival is not just a technological milestone; it is a transformative force reshaping various fields, including business, medicine, and education (Dwivedi et al., 2021).

Generative AI, is a subset of artificial intelligence, with the ability to generate new content, for example, text, images, or even audio, based on the data that it has been trained on (McKinsey, 2024). Generative AI tools have become more accessible to the public recently, and they are quickly being incorporated into various sectors and industries (Chan & Hu, 2023).In 2024, organizations began to truly harness the power of generative AI, with 65% of businesses regularly utilizing the technology according to a recent McKinsey survey (Singla et al., 2024). This is nearly twice the rate reported just ten months prior. Expectations for generative AI's impact remain high, with 75% of respondents anticipating significant or disruptive changes in their industries in the coming years (Singla et al., 2024).

The rapid development of generative AI is not only benefiting businesses; students are also among the many who are reaping its advantages. According to a survey of over 6,300 students across Germany, nearly two-thirds (63.4%) reported using AI-based tools for their studies (Von Garrel & Mayer, 2023). This quantitative analysis highlights the significant role AI is playing in education, demonstrating that a majority of students have incorporated AI tools into their academic routines.

The widespread use of generative AI tools among students has raised many concerns across academia. Concerns regarding the use of AI tools among students include ethical issues, potential for plagiarism, over-reliance on AI, data privacy, algorithmic transparency, misinformation, and the potential negative impact on students' learning and critical thinking skills (Von Garrel & Mayer, 2023; Ghimire & Edwards, 2024; Lau & Guo, 2023; Qadir, 2023; Malik et al., 2023), as well as potential threats to teacher job security, reduced student engagement in deep learning, and the need for effective motivational strategies to address challenging problems (Yilmaz & Yilmaz, 2023; Zhai et al., 2021).

Universities have always implemented rules and guidelines to safeguard their students from academic misconduct. The increased accessibility of generative AI tools has created the need for universities to prepare their students to work with and understand the principles of

Artificial Intelligence (Chan & Hu, 2023). However, most institutions currently lack specific guidelines for the ethical use of AI tools like ChatGPT (Ghimire & Edwards, 2024).

Although some research has been conducted on the needs and construction of AI policies, there remains a significant gap in understanding the varying impacts these different types of policies have on university students. Chan and Hu (2023) highlight the necessity for comprehensive research to identify the most effective ways to integrate generative AI into higher education while addressing potential privacy and security risks. Chan (2023) highlighted the importance of developing comprehensive AI education policies to prepare students for working with advanced technologies, while Ghimire and Edwards (2024) emphasized that most institutions lack specific guidelines for the ethical use of AI tools. This underscores the necessity for further research to explore how different policies influence student engagement, learning outcomes, and ethical considerations in the context of the use of AI tools in education.

Although a lot of research has been done about algorithm aversion and factors influencing algorithm aversion (Dietvorst et al., 2015; Jussupow et al., 2020; Mahmud et al., 2022), no research has been done on algorithm aversion in restrictive environments such as universities with specific policies governing the use of AI tools. The primary objective of this study is to explore the impacts of university policies on algorithmic aversion and appreciation among students. This study aims to identify factors that contribute to algorithm aversion and evaluate the effectiveness of different policy measures. The significance of this research lies in its potential to inform policy-making and educational strategies, ensuring that the benefits of AI integration are maximized while mitigating any negative impacts.

Algorithm aversion refers to the hesitation of human decision-makers to rely on algorithms that are superior but imperfect, even as algorithm-enhanced decision-making becomes increasingly common (Dietvorst et al., 2015). Although substantial research has identified various factors influencing algorithm aversion, such as perceived algorithm capabilities and human involvement (Jussupow et al., 2020; Mahmud et al., 2022), there remains a notable gap in examining how restrictive environments, such as university settings with specific AI policies, impact this phenomenon. Understanding these environments is necessary to better grasp the role university policies can have on algorithm aversion or appreciation among students. As such, we developed the following research questions: (RQ1)What are students' general attitudes towards the use of AI? (RQ2)To what extent do different university policies influence levels of algorithm aversion among students? (RQ3)Do students have different expected learning outcomes under different AI usage policies?

To address RQ1 and RQ2, we build on theories and examples by Balabdaoui et al. (2024) that highlight how students' attitudes towards AI are complex and influenced by multiple factors, including discipline, gender, and personal experience with AI tools. This study underscores the importance of developing tailored AI education policies that address these diverse perspectives and prepare students for a future where AI is ubiquitous in both academic and professional contexts. Additionally, we incorporate prior research by Heßler et al. (2022), which explains how the context in which participants make decisions affects their degree of algorithm aversion. This is further complemented by the theory from Turel and Kalhan (2023), which posits that implicit biases against AI significantly contribute to algorithm aversion, but these biases can be mitigated through positive experiences and increased familiarity with AI's capabilities. To address RQ3, we expand on this theoretical foundation by incorporating categories from the research by Yilmaz and Yilmaz (2023), which demonstrates the positive impact of generative AI tools on students' computational thinking skills, programming skills, and students motivation. By integrating these insights, we create our own measurements for expected learning outcomes, considering how AI usage policies can influence students' educational experiences and attitudes towards AI.

In sum, we posit that the current research on the use of generative AI among students has taken an important but limited approach and can benefit from adding a focus on how restrictive environments, such as universities with specific AI policies, can influence algorithm aversion among students. By investigating these contexts, our study aims to (1) examine how different university AI policies (restrictive vs. flexible) influence students' levels of algorithm aversion, (2) investigate the factors contributing to students' engagement and perceived fairness in the use of AI, and (3) assess the expected learning outcomes under different AI policy frameworks. This research will contribute to a deeper understanding of how tailored policies can shape students' interactions with AI, ultimately informing better policy-making and enhancing educational outcomes. Moreover, this study will also contribute to the research on algorithm aversion as it is the first to explore aversion under restrictive and flexible circumstances.

To address our research questions questions, we will conduct a mixed-methods study involving quantitative surveys and a document analysis of existing AI policies among Dutch universities. Our plan includes reviewing existing policies among all Dutch research universities, which we have done in two snapshots earlier this calendar year and at the end of the academic year. Based on these analyses, we developed four different policy scenarios. We then designed a survey experiment in which participants first answered demographic questions and control variables regarding their general use and attitudes towards AI. Afterward, they were presented with one of four specific scenarios, and we tested their levels of AI aversion and expected learning outcomes. The survey was conducted among Dutch university students across various institutions to ensure a representative sample. Responses were collected anonymously to encourage honest and unbiased feedback. This comprehensive survey experiment aims to provide insights into the optimal AI policies for enhancing learning outcomes while addressing students' concerns and aversions towards AI.

Chapter 2

Background

In this section, we review the literature related to artificial intelligence in education, university policies on AI, and algorithm aversion, providing the background necessary for understanding the context of this study.

2.1 AI in Education

Although AI has only recently gained significant traction, its application to education (AIED) has been a topic of academic research for over 50 years (Carbonell, 1970). Initially, AI in education was implemented through computers and computer related technologies, which were used for various tasks; administrative tasks, instruction tasks, and learning enhancement tasks. The scope of AI applications in education was defined by their technological capabilities. AI evolved into web-based and online intelligent education systems, and then into embedded computer systems, ultimately involving technologies such as humanoid robots and web-based chatbots. These advancements enabled AI to assume instructional roles, either independently or in collaboration with human instructors (Chen et al., 2020). The development of "third generation" AI, which includes generative AI, has greatly improved recognition performance by mimicking brain processes. This advancement has also had a significant impact on education. Research by Zhai et al. (2021) shows that AI was not popular in primary and secondary education before 2021. Although AI in education has been studied for many years, its widespread use only began to gain significant traction with recent developments such as the advent of ChatGPT. One of the main reasons ChatGPT is so popular is its ability to maintain a consistent conversational style and persona, which allows for more natural and realistic dialogues (Qadir, 2023). According to research by Chassignol et al. (2018), AI is now widely used by educators and students. It includes AI powered tools like teaching robots, intelligent tutoring systems, and adaptive learning systems, along with AI applications for skill building, scheduling, and career education. The rapid advancement of computing and information processing techniques has accelerated the development and use of AI, allowing computers to simulate intelligent human behaviors, such as inferencing, analysis, and decision-making (Hwang et al., 2020).

2.1.1 Current Applications of AI in Education

The rise of AI has enabled personalized learning by analyzing vast amounts of data to create customized educational experiences. This capability is essential for meeting the demands of Industry 4.0, where agility and adaptability are crucial (Abulibdeh et al., 2024). Hwang et al. (2020) highlight that a key objective of AI in education is to provide personalized learning guidance and support to individual students, tailored to their learning status, preferences, and personal characteristics. This can help students work at their own pace, guided by a personalized AI tutor that helps them with their needs. Research by Chan and Hu (2023) shows that students also acknowledge the potential of AI for personalized learning support, finding it useful for writing and brainstorming assistance, as well as for research and analysis capabilities. Qadir (2023) add to this notion by providing more examples of the usefulness of generative AI for students. For instance, ChatGPT has the potential to offer personalized and effective learning experiences by providing students with customized feedback and explanations, as well as creating realistic virtual simulations for hands-on learning. Overall, a significant number of students are already using AI-based tools for their studies, with 63.4% of students surveyed reporting their use of such tools, and an average familiarity with chat and translation tools among students (Von Garrel & Mayer, 2023; Balabdaoui et al., 2024).

Teachers can also benefit from AI, as it can provide intelligent systems that assist with assessments, data collection, enhancing learning progress, and developing new strategies (Hwang et al., 2020). These AI systems can help reduce the workload of educators by automating routine tasks, allowing them to focus more on personalized instruction and student engagement. Additionally, AI can offer valuable insights through data analysis, helping teachers identify areas where students may need extra support or enrichment. Moreover, a study by Yilmaz and Yilmaz (2023) shows that AI tools can greatly benefit students. Their research demonstrated that tools such as ChatGPT can improve students' computational thinking skills, programming self-efficacy, and motivation for lessons.

2.1.2 Challenges of AI in Education

The widespread use of AI tools among students also brings challenges. While AI can personalize learning experiences, provide real-time support, and offer instant feedback, it also raises some issues. Abulibdeh et al. (2024) highlight concerns regarding the digital divide, bias, privacy, overreliance on technology, and resistance to change.Abulibdeh et al. (2024) also highlight that relying too much on AI tools can reduce students' critical thinking and problem-solving abilities, and can also prevent them from learning from mistakes and setbacks. Concerns also include the reduction of social interaction and the possibility of hindering the development of general skills. Chan (2023) advocate for the need for a comprehensive AI policy in higher education that addresses the potential risks and opportunities associated with generative AI technologies.

2.1.3 Changing the Way Students Are Assessed

The integration of AI in education requires a re-evaluation of traditional assessment methods. This re-evaluation is necessary to ensure the fairness and accuracy of assessments in an

AI-enhanced educational environment. For instance, Chan and Hu (2023) and Balabdaoui et al. (2024) suggest that exams need to be designed to ensure that AI tools cannot simply provide the answers, thus requiring students to demonstrate deeper understanding and critical thinking. To balance these concerns, it is important to consider how AI can be used constructively in the learning process. Many students surveyed by Balabdaoui et al. (2024) indicated that AI might be effective during exam preparation and assignments, suggesting it should be integrated into the learning process. Overall, the adoption of AI in education calls for strategic policy-making to harness its benefits while mitigating potential downsides, ensuring that AI technologies are used responsibly to enhance learning outcomes and uphold academic integrity.

2.2 University Policies

The rapid advancement of artificial intelligence (AI) technologies presents both significant opportunities and challenges within the education sector. UNESCO (2021) highlight that these advancements hold the potential to transform teaching and learning practices, thereby accelerating progress towards their proposed Sustainable Development Goal 4 (SDG 4), which aims to ensure inclusive and equitable quality education and promote lifelong learning opportunities for all. However, the swift pace at which these technologies evolve often surpasses the capacity of policymakers to adequately respond, leaving a gap in the necessary regulatory frameworks (Dwivedi et al., 2021).

2.2.1 The Urgent Need for AI Education Policies

The integration of generative AI tools, which have become increasingly accessible, into various educational contexts underscores the urgent need for comprehensive AI education policies. Such policies are essential for preparing students to work with and understand the principles of AI technology (Chan, 2023). As AI applications in education proliferate, they raise issues that need to be addressed through thoughtful policy-making. These issues include data ownership, consent, privacy, and the potential for algorithmic biases that may undermine human rights (UNESCO, 2021).

Researchers and policy experts unanimously recognize the necessity of these policies. For instance, administrators highlight the importance of safeguarding student safety and mitigating plagiarism risks (Ghimire & Edwards, 2024). Moreover, the rapid deployment of AI in education necessitates addressing ethical concerns, such as discrimination, bias, and the protection of human rights (Chan & Hu, 2023). The potential for malicious use of AI further emphasizes the need for robust regulatory frameworks (Abulibdeh et al., 2024).

2.2.2 Current Landscape and Gaps in AI Policies

Despite these acknowledged needs, the current landscape reveals that policy development has struggled to keep pace with technological advancements. In 2018, there were virtually no policies addressing the ethical issues posed by AI in education (Holmes et al., 2019). Even today, the development of comprehensive AI policies is still in its nascent stages, with many institutions either actively working on policies or lacking them altogether (Dwivedi et al., 2021).

The absence of these policies poses risks, such as data misuse and academic dishonesty, which can significantly impact students (Ghimire & Edwards, 2024). Therefore, it is critical to develop policies that promote the ethical use of AI in education, ensuring that AI tools are used to enhance learning while preserving critical thinking and creativity (UNESCO, 2021).

2.2.3 Strategies for Effective Policy Development

Effective AI policies should involve a collaborative approach, engaging key stakeholders including educators, students, AI developers, and policymakers (Abulibdeh et al., 2024). This collaborative effort should aim to create AI systems that align with educational objectives and pedagogical principles. Additionally, policies should ensure transparency, accountability, and inclusivity, addressing biases and ensuring equitable access to AI technologies (UNESCO, 2021).

In conclusion, while AI has the potential to revolutionize education, its integration must be guided by well-developed policies that address ethical concerns and promote inclusive and equitable access. The development of these policies is critical for harnessing the benefits of AI while mitigating its risks, thereby ensuring that AI contributes positively to educational outcomes and aligns with societal values.

2.3 Algorithm Aversion

Algorithm aversion refers to the tendency of individuals to prefer human judgment over algorithmic predictions, even when the latter are demonstrably more accurate (Dietvorst et al., 2015). Research comparing the effectiveness of algorithmic and human forecasts consistently shows that algorithms outperform humans. The research on algorithm performance begins with the research by Meehl (1954). In his book "Clinical Versus Statistical Prediction: A Theoretical Analysis and Review of the Evidence," Meehl (1954) analyzed results from 20 forecasting studies across various fields, including academic performance and parole violations. His findings revealed that algorithms outperformed their human counterparts. Although Meehl's research did not specifically address algorithm aversion, it laid the groundwork for subsequent studies and marks the start of AI aversion research, investigating why individuals continue to prefer human judgment despite the superior performance of algorithms.

Building on Meehl's findings, Dietvorst et al. (2015) introduced the concept of algorithm aversion, highlighting significant psychological and cognitive barriers to the adoption of superior algorithmic solutions. This phenomenon, known as algorithm aversion, describes the tendency for people to reject algorithmic advice after witnessing algorithmic errors, despite the fact that algorithms generally provide more accurate predictions than human forecasters. Dietvorst et al. (2015) found that individuals quickly lose confidence in algorithms after witnessing them make mistakes, a tendency not observed with human forecasters.

2.3.1 Factors Influencing Algorithm Aversion

Subsequent studies have expanded on this concept, identifying various cognitive and psychological factors that exacerbate algorithm aversion. For example, Turel and Kalhan (2023) found that people hold an implicit bias against AI in terms of its untrustworthiness, driving algorithm aversion even after accounting for relevant explicit attitudes. Similarly, Mahmud et al. (2022) emphasized the role of cognitive biases, suggesting that individuals' faulty assumption that algorithms cannot learn from mistakes significantly contributes to algorithm aversion.

Shin et al. (2020) explored how different algorithmic features—such as fairness, accountability, transparency, and explainability—affect users' perceptions and trust in personalized machine learning algorithms. Their findings reveal that algorithmic features play a crucial role in shaping user trust and behaviors through a dual-process evaluation. The dual-process model describes two modes of user assessment: heuristic and systematic. Heuristic processes involve quick, intuitive judgments based on algorithmic features, while systematic processes involve more deliberate, thorough evaluations. Both processes are positively associated with trust, with systematic evaluations also linked to expectations of performance and emotional responses.

An empirical study by Workman (2005), applied the Theory of Planned Behavior to investigate decision support algorithms. The findings revealed that using these algorithms was associated with fewer errors, while misuse led to more errors. Positive attitudes and social influences promoted algorithm use, whereas perceptions of control had no significant impact. The study also identified a significant non-linear interaction between social influences and attitudes affecting algorithm misuse, highlighting the role of user attitudes and social context in the effective use of decision support algorithms.

In a related study, Heßler et al. (2022) explored how context influences algorithm aversion. Their research found that users exhibit greater algorithm aversion in decision-making situations that are for helping others (like charity) compared to those aimed at making a profit. This aversion arises because users value empathy and autonomy more in prosocial settings, leading to a stronger preference for human-like decision support. Their findings suggest that making decision support systems more human-like could reduce algorithm aversion, especially in contexts where self-humanization is important.

2.3.2 Mitigating Algorithm Aversion

Despite the general trend of algorithm aversion observed by Dietvorst et al. (2015), some researchers have identified conditions under which this aversion can be mitigated. Reich et al. (2023) found that emphasizing an algorithm's capacity to learn from its mistakes can significantly reduce algorithm aversion, enhancing trust and consequential choice in algorithms. Their study demonstrated that when consumers are made aware that algorithms, like their human counterparts, can learn from their errors, they are more likely to trust and use algorithmic advice. Chen et al. (2020) examined ways to reduce algorithm aversion by exploring the effects of different types of control. Their research found that providing users with outcome control—where users have a say in how model predictions are used in decision-making—helps to reduce algorithm aversion.

2.3.3 Algorithm Appreciation

Contrary to the predominant focus on algorithm aversion, Logg et al. (2019) identified a phenomenon of 'algorithm appreciation,' where individuals showed a preference for algorithmic over human judgment in specific contexts. This finding suggests that the context and presentation of algorithmic advice play crucial roles in influencing user acceptance. Additionally, Castelo et al. (2019) suggested that increasing the perceived human-likeness of algorithms can reduce resistance, particularly for subjective tasks, indicating that the design and framing of algorithms are critical factors in mitigating aversion.

Overall, understanding the psychological and cognitive factors contributing to algorithm aversion is essential for developing strategies to enhance the adoption of algorithmic solutions. By addressing these factors through targeted interventions, such as emphasizing the learning capabilities of algorithms and designing human-like interfaces, it is possible to reduce aversion and improve the integration of algorithms in various decision-making contexts.

Chapter 3

Hypothesis

This chapter presents the hypotheses derived from the theoretical background and literature review discussed in the previous chapters. Each hypothesis is formulated to address the specific research questions posed in this study. The research mentioned in the background section was used to derive preregistered hypotheses.

Trust in AI systems is crucial for their acceptance and effective use. According to Shin et al. (2020), algorithmic characteristics such as fairness, accountability, transparency, and explainability (FATE) are fundamental in building user trust. They state, "The results indicate the heuristic roles of algorithmic characteristics in terms of their underlying links to trust and subsequent behaviors. Users experience a dual-process in assessing AI features and formulating trust through their heuristic-systematic evaluations"(Shin et al., 2020). By implementing policies that emphasize these characteristics, universities can significantly influence students' trust in AI.

Furthermore, Shin et al. (2020) highlight that "transparency, fairness, and accuracy play critical roles in algorithm services by improving user trust in algorithms". This suggests that university policies that promote these values can enhance students' trust in AI systems. Thus, we posit:

H1a: *Universities' AI Policies influence participants' trust in AI.*

Positive attitudes towards AI are essential for its adoption and effective integration in educational settings. Shin et al. (2020) discuss how heuristic and systematic processes shape user experiences and interactions with AI, noting that "Heuristic and systematic processes offer a useful perspective on the conceptualization of AI experience and interaction". These processes help form user attitudes towards AI.

Shin et al. (2020) further state, "The model illustrates that interacting with algorithms involves a set of interrelated cognitive processes wherein features of algorithms are used to formulate a heuristic of user motivation and to trigger action in AI services". Policies that support transparent, fair, and accurate AI systems can positively influence these cognitive processes, shaping more favorable attitudes towards AI. Therefore, we hypothesize:

H1b: *Universities' AI Policies influence participants' attitudes Towards AI.*

Higher levels of trust in AI are likely to reduce algorithm aversion. Turel and Kalhan (2023) suggest that biases against AI influence trust levels, noting that "People hold (on average) an implicit bias against AI in terms of its untrustworthiness" and this bias "drives algorithm aversion even after accounting for relevant explicit attitudes" . Therefore, increasing trust in AI can mitigate these biases and reduce algorithm aversion. Hence, we posit:

H2a: *Participants with higher trust in AI will exhibit lower levels of algorithm aversion.*

Algorithm aversion, the reluctance to trust and use algorithms, can be mitigated by fostering positive attitudes towards AI. Workman (2005) found that "people's perceptions and attitudes towards algorithms are strongly associated with algorithm aversion". This suggests that improving attitudes towards AI can reduce aversion.

Turel and Kalhan (2023) support this by indicating that implicit biases against AI drive algorithm aversion: "People hold (on average) an implicit bias against AI in terms of its untrustworthiness" and this bias "drives algorithm aversion even after accounting for relevant explicit attitudes". By addressing these biases and promoting positive attitudes, algorithm aversion can be reduced. Thus, we hypothesize:

H2b: *Participants with more positive attitudes towards AI will exhibit lower levels of algorithm aversion.*

University policies play a crucial role in shaping students' perceptions and acceptance of AI. Jussupow et al. (2020) highlight the phenomenon of algorithm aversion, noting that "users are reluctant to interact with algorithms instead of human agents." They also emphasize that various factors, such as algorithm performance, perceived capabilities, and the level of human involvement, influence whether users develop aversion to algorithms.

Heßler et al. (2022) further elaborate that algorithm aversion is significantly influenced by the context in which decisions are made. Specifically, contexts perceived as more personally relevant, such as prosocial decision-making, heighten the perceived need for empathy and autonomy, which in turn increases algorithm aversion. Given these insights, Jussupow et al. (2020) suggest that factors such as algorithm agency, performance, and the social distance between human agents and users are critical in shaping algorithm aversion. By implementing university policies that address these factors and promote human-like attributes in AI systems, institutions can effectively influence and potentially reduce students' levels of algorithm aversion. Therefore, we posit:

H3: *Universities' AI Policies Influence participants' levels of Algorithm Aversion.*

Algorithm aversion significantly impacts the usage of AI tools. Dietvorst et al. (2015) found that "people tend to rely less on algorithms even when algorithms provide better decisions" (p. 1). This aversion is often triggered by the visibility of errors, as "algorithm aversion is often triggered by the visibility of errors, which can be more impactful than the actual frequency of errors" (Dietvorst et al., 2015).

Given that students' aversion to algorithms can negatively affect their willingness to use generative AI tools, it is important to address these concerns to enhance AI adoption. Therefore, we hypothesize:

H4: *Algorithm Aversion has a significant negative influence on the use of generative AI tools by students.*

Educational theories on personalized learning, student engagement, and self-efficacy Yilmaz and Yilmaz (2023) suggest that AI tools like ChatGPT, which provide tailored learning experiences and instant feedback, significantly enhance learning outcomes. Moreover, Chan and Hu (2023) emphasize the importance of understanding student perceptions to tailor AI use for effective learning. They propose a framework that includes pedagogical, governance, and operational dimensions, arguing that well-informed policies can positively influence student attitudes towards AI. Their research reveals that students generally perceive AI technologies positively, recognizing their potential to provide personalized learning support and immediate feedback, which are critical for enhancing learning outcomes. These findings align with Yilmaz and Yilmaz (2023) observations that AI's interactive nature boosts student motivation and engagement. Additionally, the supportive nature of AI tools improves students' self-efficacy, a crucial predictor of academic performance. By providing real-time assistance and addressing individual learning needs, AI tools help students develop confidence in their abilities, leading to better learning outcomes.

Integrating these theoretical insights, we hypothesize that AI use in educational settings will positively influence expected learning outcomes. Thus, we posit:

H5: *The use of generative AI tools in educational environments will result in a significant and positive enhancement of students' expected learning outcomes.*

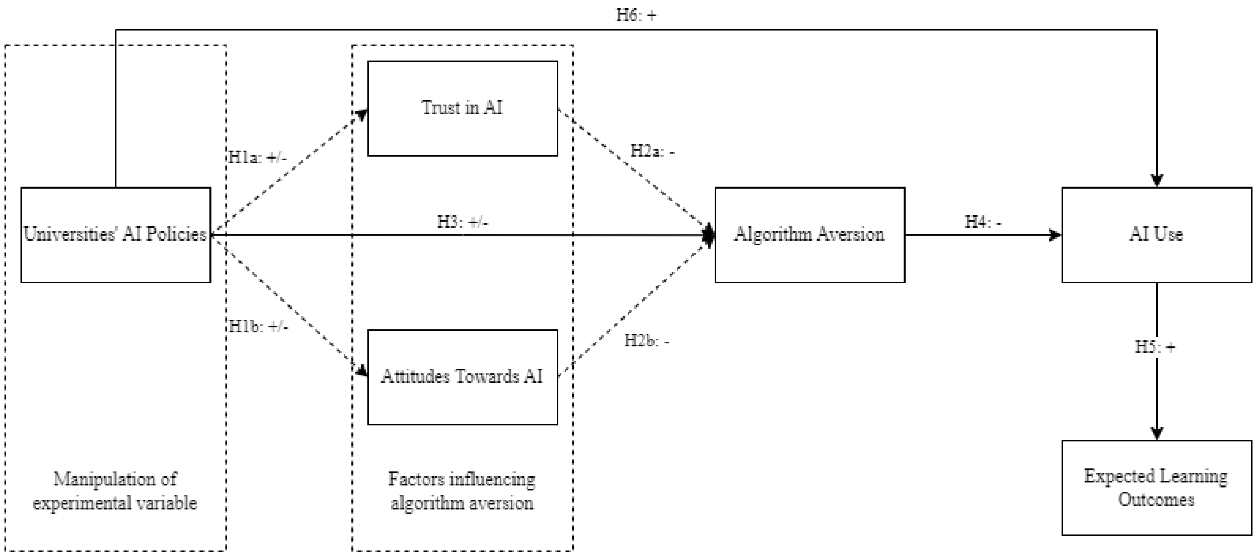
Universities' AI policies can significantly influence the extent to which AI tools are utilized by students. Policies that promote transparency, fairness, and accountability in AI systems are likely to enhance students' willingness to use these tools. Shin et al. (2020) emphasize the importance of these characteristics, stating that "transparency, fairness, and accuracy play critical roles in algorithm services by improving user interaction with AI". By implementing policies that focus on these aspects, universities can directly encourage the use of AI tools.

Furthermore, university policies that address students' concerns about AI and actively promote its benefits can lead to increased usage. Chan (2023) suggest that understanding and addressing student perceptions of AI is crucial for fostering effective AI integration in educational settings. They state, "Policies can positively influence the perspectives of students towards AI, thereby encouraging its use" (Chan, 2023). Thus, well-crafted policies can directly enhance AI usage by creating a more supportive and informed environment for students. Therefore, we hypothesize:

H6: *Universities' AI Policies influence AI use.*

Figure 3.1 illustrates the theoretical framework that we have developed in this section. Illustrating the hypothesized relationships between universities' AI policies, trust in AI, attitudes towards AI, algorithm aversion, AI use, and expected learning outcomes.

Figure 3.1:
Theoretical Framework



Note: Theoretical framework illustrating the hypothesized relationships between various factors influencing AI use and expected learning outcomes.

Chapter 4

Methods

In this section, we outline the methodologies employed to address the research questions posed in this study. Detailed descriptions of the research design, data collection, and data analysis procedures are provided to ensure transparency and reproducibility of the study. Each step of the methodological process is carefully explained to give a clear understanding of how the research was conducted and how the conclusions were derived.

4.1 Selection of Methodology

To answer the research question, a mixed-methods research design, combining document analysis and a scenario-based survey, was employed. This approach was chosen to provide a comprehensive and nuanced understanding of university AI policies and their potential impacts on students. Initially, a purely qualitative design was considered. However, due to time constraints and difficulties in engaging a diverse sample of students across different universities, we integrated quantitative elements to enhance the robustness of the findings. The study began in February 2024 with the collection and analysis of AI-related policies from all 13 Dutch research universities These policies were analyzed and categorized to capture the various perspectives and approaches adopted by different institutions. A scenario-based survey was then conducted. Participants were presented with one of four different imaginary university AI policies derived from the analyzed real-world policies, including policies categories from both March and July to capture the potential impacts of policy changes over time. This method allowed for an empirical assessment of students' perceptions and reactions to different types of AI policy scenarios.

The rationale for selecting this mixed-methods approach includes several key considerations. Firstly, it ensures comprehensive understanding by combining document analysis, which provides a thorough examination of current AI policies, with a scenario-based survey that systematically measures student responses, offering both depth and breadth to the study. Secondly, it integrates theory and practice by grounding the survey scenarios in real-world policies, ensuring that the findings are relevant and applicable to actual educational settings, thus bridging the gap between theoretical insights and practical implications. Lastly, this approach captures the complexity of institutional policies and measures their practical impact, providing insights that are crucial for policy formulation and implementation.

4.2 Document Collection

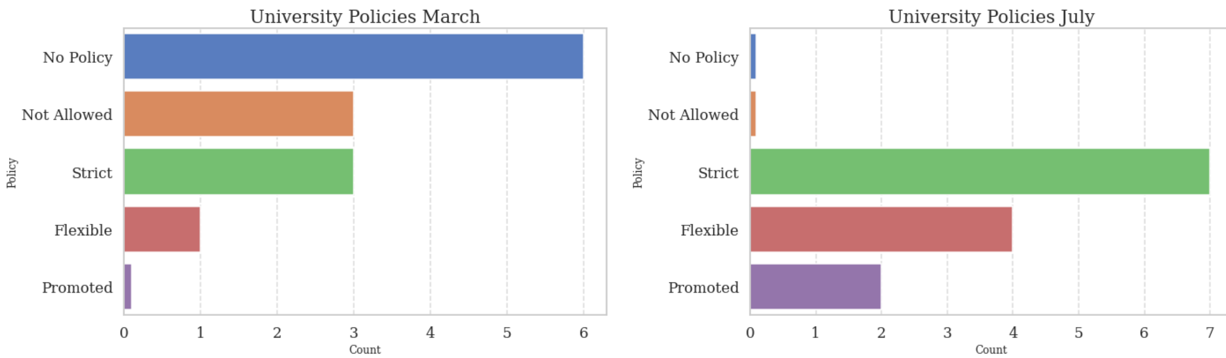
To gather information on the different policies of universities regarding AI, we consulted a range of sources. These included university websites, which provided detailed policy documents, guidelines for students and instructors, official examination regulations, and communications directed at students. Only official university domains were used to ensure the credibility and authenticity of the documents. We cross-referenced these documents where possible with official announcements and guidelines provided by the universities to ensure their accuracy. This comprehensive approach ensured a thorough understanding of the AI-related guidelines and regulations set forth by universities for coursework, research, academic projects, and exams. We decided to include all 13 Dutch research universities to ensure a representative sample of the diverse approaches to AI policy in higher education in the Netherlands. We collected the data in two different snapshots: the first data collection was conducted on February 5, 2024, coinciding with the end of the first semester, and the second was carried out on July 14, 2024, coinciding with the end of the academic year. These dates were chosen to capture policy changes over the academic year.

4.3 Document Analysis

For each university, we searched the web for relevant documents, extracted the sections related to AI use by students or guidelines for instructors, and compiled this information into an Excel spreadsheet. The data were then categorized into one of five categories: Banned or Not Allowed, where AI use is completely prohibited under any circumstances; Strict Policies with Mandatory Guidelines, where AI use is prohibited unless explicitly permitted and violations are treated as serious misconduct; Flexible Policies with Optional Guidelines, which allow AI use under certain conditions with guidelines for responsible use and proper attribution; Allowed and Promoted, encouraging AI use and integrating it into learning activities with requirements for proper attribution; and No Policy, indicating universities with no specific AI policy in place. Universities with no available documents were labeled as having no policy. We utilized GPT-4 for preliminary classification of policy documents to identify key sentences. The author manually verified these classifications to ensure accurate categorization of the policies. The results of the document analysis can be seen in 4.1. This table provides an overview of the different AI policies across the 13 universities, highlighting changes and trends observed between the two snapshots.

As can be seen in 4.1 In March, the majority of universities (6) had no specific AI policy. By July, there was a notable shift: all universities had implemented AI policies, with the majority (7) adopting strict policies. Additionally, no universities maintained a complete ban on the use of AI, recognizing the integral role AI will play in the future. Notably, 4 universities adopted flexible policies and 2 universities even adopted promotive policies encouraging the use of AI by students. The overall trend indicates a growing acknowledgment among universities of the importance of AI integration in education.

Figure 4.1:
Comparison of AI Policies in March and July.



(a) *Count of AI Policies (March)* (b) *Count of AI Policies (July)*

Note: The March data shows most universities with no AI policies and several with not allowed policies, whereas the July data indicates a shift towards more lenient policies, with more flexible and some promotive policies adopted.

4.4 Survey Participants

A total of 156 replies were initially received. After eliminating participants with incomplete responses (n = 18), those who completed the survey too quickly, suggesting a lack of careful and thoughtful answering (n = 4), and those who straightlined their responses by selecting the same option repeatedly (n = 2), we were left with 125 valid responses. In total, 24 participants were excluded, accounting for 15.4% of the initial sample. Of the 125 valid responses, 68.0% (n = 85) also answered the additional questions.

The mean age of these 102 participants was 28.97 years ($SD = 10.53$). Among the participants, 48 identified as male, accounting for 38.40% of the total sample. Female respondents were the largest group, with 69 participants representing 55.20%. Three respondents, or 2.40%, identified as non-binary or third gender. Additionally, five participants, or 4.00%, preferred to self-describe their gender. No respondents chose the "Prefer not to say" option.

Table 4.1 details the educational background of the respondents, based on a total sample size of 125 individuals. The majority of respondents, 39.20%, have attained a University Bachelor's Degree. A substantial 29.60% hold a Graduate or Professional Degree (e.g., MA, MS, MBA, PhD). The category of "Some University but no Degree" comprises 12.80% of respondents. Additionally, 11.20% have completed secondary school, and 7.20% fall into the "Other" category, which includes various non-standard educational qualifications. This distribution indicates a predominantly well-educated sample.

Table 4.2 details the distribution of educational fields among the study participants (N = 125), reflecting a diverse array of academic backgrounds. The largest representation is in Economics and Business, comprising 32 participants (25.6%). This is followed by Engineering

Table 4.1:
Level of Education of Respondents

Level of Education	Frequency	Percentage (%)
University Bachelor's Degree	49	39.20
Graduate or Professional Degree (MA, MS, MBA, PhD)	37	29.60
Some University but no Degree	16	12.80
Completed secondary school	14	11.20
Other	9	7.2

Note. This table presents the level of education of respondents, including frequencies and percentages based on the total sample (N = 125).

and Technology, with 22 participants (17.6%), and Arts and Design, with 15 participants (12.0%). These findings indicate a broad range of study fields within the sample.

4.5 Survey Procedure

To understand students' perceptions of AI in education, an experimental design survey was developed following the initial document analysis. Based on the policies derived from the 13 Dutch universities, four imaginary AI policies were created: a strict usage policy, an encouraged usage policy, a flexible policy, and a baseline policy with no specific rules or regulations regarding the use of generative AI tools. For more details, see Appendix B. The survey instrument was developed and validated through several iterations of pilot studies with 5 participants each. These pilot studies helped refine the survey questions for clarity and relevance, ensuring the reliability and validity of the survey.

4.5.1 Control Variables

The demographic part of the survey collected data on participants' age, gender, highest level of education, and primary field of education. To capture participants general attitudes towards AI we asked them about their experience with AI tools and specific types of AI tools based on questions from Balabdaoui et al. (2024). Additionally, the survey included an optional section where participants could share their general opinions on AI.

4.5.2 Independent Variables and Control Variables

Participants were randomly assigned to one of the four university policies in a between-subjects experimental design. (See Appendix B for the experimental stimuli.) We derived control variables directly from research on algorithm aversion by Turel and Kalhan (2023), familiarity with AI, explicit attitudes towards AI and trust in AI. To measure algorithm aversion, we included several different constructs taken from the literature. The first way to measure participants general algorithm aversion is through the user's choice algorithm

Table 4.2:
Distribution of Fields of Education

Field of Education	Frequency	Percentage (%)
Economics and Business	32	25.6
Engineering and Technology	22	17.6
Arts and Design	15	12.0
Social Sciences	15	12.0
Other (Please specify):	10	8.0
Health and Medical Sciences	9	7.2
Education	8	6.4
Humanities	6	4.8
Law	4	3.2
Prefer not to say	2	1.6
Environmental Sciences	1	0.8
Natural Sciences	1	0.8

Note. This table presents the distribution of fields of education among the study participants. The frequencies and corresponding percentages are based on the total sample. (N = 125)

aversion measurement, which was roughly adapted from Heßler et al. (2022). We used a 7-point Likert scale where participants were asked to indicate their preference for human support versus computerized support in helping them with academic assignments. The alternative approach we took to measure algorithm aversion was grounded in research by Turel and Kalhan (2023), where we measured participants' implicit attitudes towards AI under the given policies, thereby indirectly measuring their algorithm aversion. The third approach we employed was our own method, using a 7-point Likert scale, asking participants to indicate whether they would use AI tools for studying under the given policies. Our scale for expected learning outcomes is anchored in research by Yilmaz and Yilmaz (2023). We have adapted Yilmaz's learning categories to develop a set of five questions, each rated on a 7-point Likert scale. The categories we incorporated include: creativity, algorithmic thinking, cooperativity, critical thinking, and problem-solving.

4.5.3 Survey Distribution

The survey was distributed through various channels, including word-of-mouth in study groups, academic networks, and social media platforms, beginning on July 7, 2024, coinciding with the end of the academic year and the survey concluded three weeks later on July 28, 2024. All submissions were anonymous, and participants were informed that the survey concerned the impact of universities' policies on algorithm aversion among students and that it would take approximately five minutes to complete. They were assured of confidentiality and provided informed consent at the start of the survey. Participants were entered into a raffle for 5 gift cards, each worth 20 euros, for completing the experiment. The survey was conducted using the Qualtrics platform (https://www.qualtrics.com).

4.6 Survey Data Analysis

Data analysis was performed using Python, utilizing the pandas, seaborn, matplotlib, and statsmodels libraries. After cleaning the data we started with a descriptive data analysis. Followed by calculating standardized factors for each multi-scale construct based on the associated items. We then calculated the mean and standard deviation for all Likert-scale questions.

Multiple linear regression models were constructed for each dependent variable, in total we used 7 different models. The regression models included dummy variables for AI policy scenarios as the primary independent variables. The baseline scenario was the "no specific policy" condition, against which the other policy scenarios (strict usage policy, flexible usage policy, and encouraged usage policy) were compared. Control variables such as age, gender, level of education, and general trust in AI were also included to account for potential confounding effects. The dependent variables were AI aversion scores, expected learning outcomes, preferences for AI-supported learning, and attitudes towards AI.

Table 4.3:
Variance Inflation Factor (VIF) Results

Variable	VIF
const	73.96
Age	1.56
Gender	1.21
Level_of_Education	1.44
Attitude_towards_AI_control	2.67
Trust_in_AI_control	1.69
Familiarity_of_AI_Tool	2.04
Use_of_AI_based_Tool	2.24
TrustAI_1_study	1.33
TrustAI_2_study	1.19
Attitude_towards_AI_Study	2.30
Allowed_and_valued	1.67
Allowed_unless	1.57
Not_allowed	1.58

Note. This table presents the Variance Inflation Factor (VIF) values for all the independent variables included in the 7 different regression models.

First, for each dependent variable, a linear regression model was specified incorporating dummy variables representing the AI policy scenarios along with control variables. The models were estimated using ordinary least squares (OLS) to determine the coefficients for each independent variable. These coefficients reflect the impact of each AI policy scenario on the dependent variable while controlling for other factors in the model. The results were interpreted by examining the significance and magnitude of the coefficients for the dummy variables. A significant positive or negative coefficient indicates that the corresponding AI policy scenario has a meaningful impact on the dependent variable compared to the baseline scenario, which was the "no specific policy" condition. Finally, residual analysis and multicollinearity checks were conducted to ensure the validity of the regression models. Variance Inflation Factors (VIF) were calculated to assess multicollinearity among the independent variables, see Table 4.3, ensuring that the regression estimates were reliable and not distorted by excessive correlation between predictors.The VIF results indicate that most variables exhibit low to moderate multicollinearity, with VIF values well below the threshold of 10, suggesting that multicollinearity is not a severe issue in the regression models.

For all dependent and independent variables, we also calculated the mean and standard deviation across the different AI policy scenarios. We compiled these descriptive statistics into a single table for control variables and another for study variables, as detailed in 5. This approach allowed for a comprehensive overview of the impact of different AI policy scenarios on both control and study variables.

Chapter 5

Results

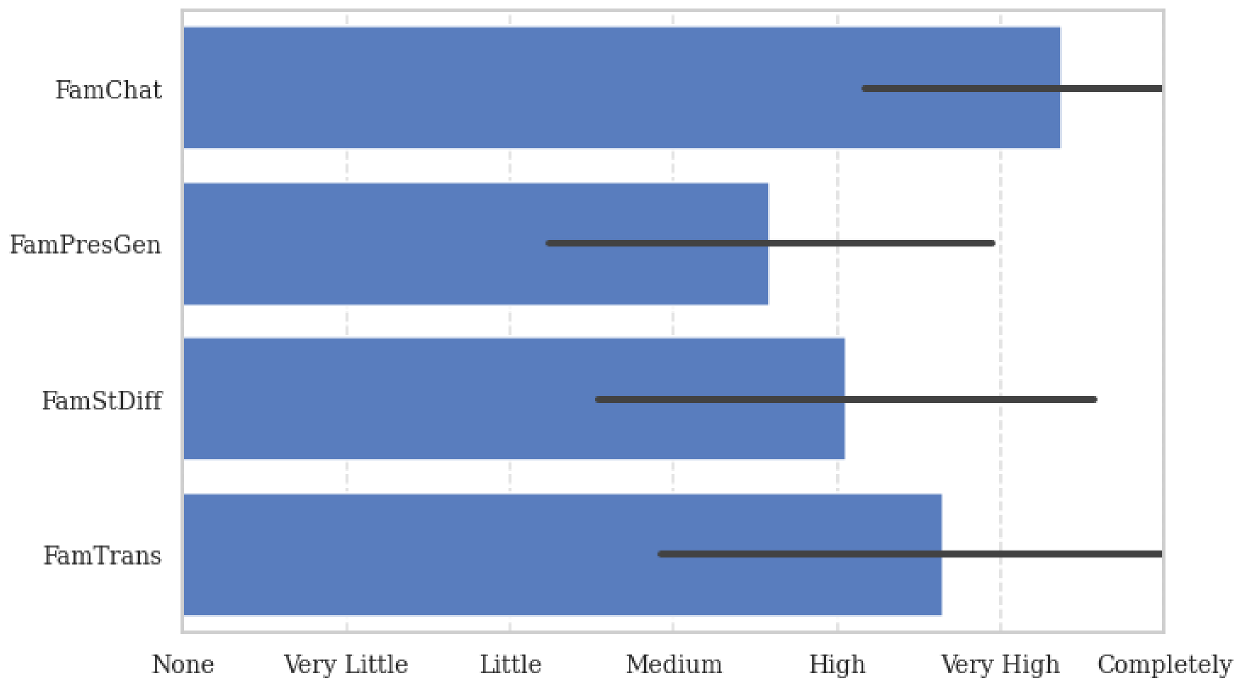
In this section, we delve into the findings of our study. We present the results from data analysis and participant input. Through a thorough examination of these results, we aim to uncover key trends and implications relevant to our research objectives. This comprehensive overview will deepen our understanding of the topic and its significance. We first report the overall demographics of our sample including age, gender, level of education and education type. After cleaning and preparing the data we were left with N = 125 valid responses.

5.1 General Attitudes Towards AI

Figure 5.1 presents participants' familiarity with various AI tools. On average, students report a very high level of familiarity with chat and high-very high level of familiarity translation tools. Additionally, their familiarity with image and presentation generation tools is respectively medium-high and high. The large standard deviations observed in these self-assessments of familiarity suggest significant variability in experience and comfort levels among the students. Our open-ended question about the use of additional AI tools revealed that participants reported utilizing a variety of specific AI tools for diverse purposes. For text summarization, tools such as SciSummary were mentioned. Elicit was noted for search and classification tasks, while Writefull is employed for language checking purposes. In the realm of coding, respondents highlighted the use of Codeium and GitHub CoPilot for file summarization. Additionally, DreamGen is utilized for image generation, and Gemini is employed for text generation. For data science, participants reported the use of diverse machine learning tools. Canva and Midjourney were mentioned for creating visual content. These responses showcase the diverse applications of AI tools in both academic and everyday settings, reflecting their widespread use and adaptability across multiple fields.

As shown in Figure 5.2, participants generally have a mixed but moderately positive outlook on AI. There is a small sense of optimism regarding the potential of AI (OpPotential), with on average participants feeling somewhat hopeful about its future, though this is accompanied by a large standard deviation, indicating varied opinions. The perceived advantages of AI usage (OpUsage) receive considerable support, indicating that participants recognize the benefits of AI technologies. The global impact of AI (OpGlobal) is viewed optimistically by some, though opinions vary widely, as reflected by the significant standard

Figure 5.1:
Familiarity with AI Tools



Note: This figure illustrates participants' familiarity with various AI tools.

deviations. Participants express approval for the continued development of AI (OpGenDev), suggesting a broad endorsement for ongoing innovation in the field. However, there are concerns about exclusion and discrimination (OpExcl), where participants feel more uneasy and worried, with large standard deviations indicating significant variability in these concerns. These variables collectively contribute to the overall measure of participants' opinions on AI.

Participants were also encouraged to present additional opinions on AI. Participants note that AI can severely impact students' creative thinking. For instance, one participant mentioned, "I feel like students, and even more future students, will think less and less by themselves because of AI. It would be nice to have guidelines to keep them from overusing it but I don't know how it would be possible." Another echoed this sentiment, stating, "It has so many benefits, but at the same time it makes students lazier, because they are no longer challenged to think for themselves, be creative and innovative."

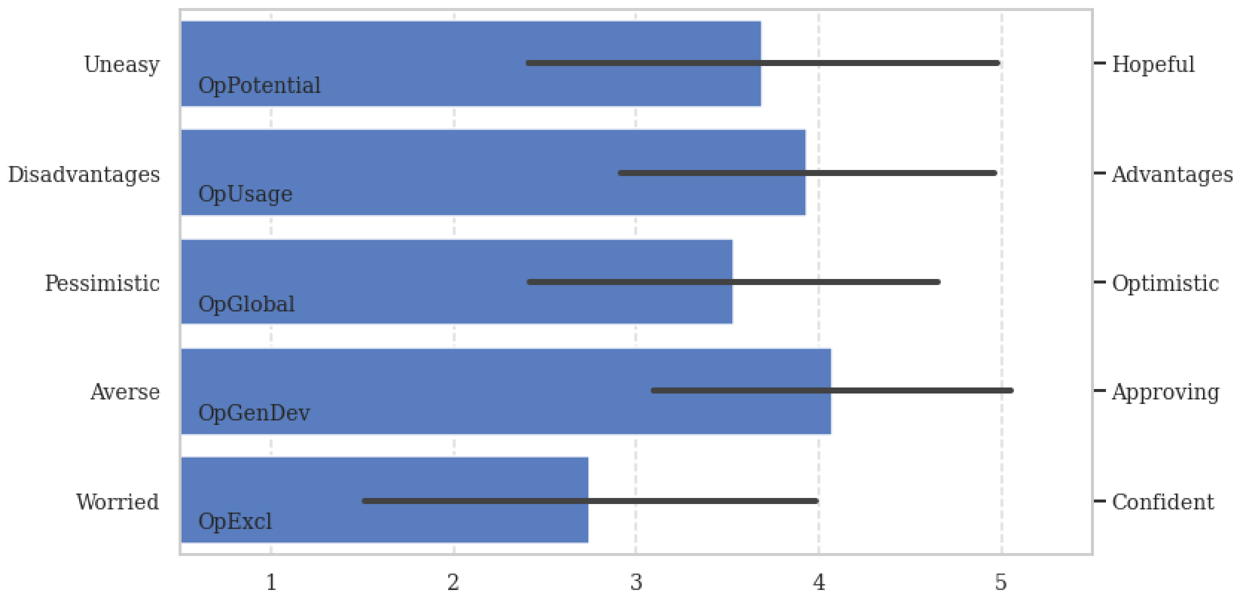
Moreover, there is a concern about academic integrity, with one participant observing, "The majority of students still fail to notify AI use in their work correctly, leading to failing classes or in extreme cases expulsion." However, some students demonstrate an awareness of the need for critical engagement with AI. One participant shared, "I use AI as a tool to co-create with. This means that I give it a prompt, then it gives me an answer and from that answer I critically reflect if it makes sense or not for me." Another emphasized the importance of verification, stating, "I ask for sources and then I verify the sources or if it does not provide me with the sources, then I search for the main phrase in Google to see if it makes sense." Participants also recognize the necessity for public awareness regarding

AI's fallibility. One noted, "There needs to be the general knowledge for the public that AI must be wrong sometimes."

A significant concern is that policy makers are lagging behind AI development. As one participant highlighted, "Legislation is lagging behind. In education, schools should interview random students how they got to their answers and whether they understand it. This to make sure students use AI to make them understand the problem." Another pointed out, "AI is unavoidable and not a bad thing, but what worries me a bit is that lawmakers are steps behind the developers of AI."

Overall, while recognizing AI's potential benefits, these insights underscore the importance of developing guidelines, enhancing critical thinking, and updating legislation to ensure responsible and effective use of AI in education.

Figure 5.2:
General Opinions on AI



Note: This figure represents the general opinions of participants regarding AI.

Table 5.1 summarizes the descriptive statistics of the control variables asked to the participants. As Table 5.1 shows, on the 7-point Likert scale, participants had an above-average familiarity with AI tools (M = 3.71, SD = 1.45). The moderately large standard deviation indicates considerable variability, suggesting that participants have differing levels of familiarity with AI tools. The use of AI for study purposes also scored above average (M = 3.40, SD = 1.70), with a large standard deviation, reflecting mixed responses among participants regarding their use of AI for studying. Participants demonstrated a generally positive attitude toward AI (M = 4.18, SD = 0.92), with less variability in responses. Lastly, the level of trust in AI was moderate low(M = 3.02, SD = 1.17).

Table 5.2 presents the descriptive statistics for the study variables across different policy conditions, as reported by participants after being exposed to the experimental stimuli. Notably, in the "Not allowed" scenario, where AI use was explicitly prohibited and deemed a

Table 5.1: Descriptive Statistics Control Variables
Means and Standard Deviations

Control Variable	Mean	Standard Deviation
Familiarity with AI Tools	3.71	1.45
Use of AI-based Tools	3.40	1.70
Attitude towards AI	4.18	0.92
Trust in AI	3.02	1.17

Note. This table presents the means and standard deviations for the control variables based on Likert-scale questions (N = 125).

punishable academic offense, the AI Use Likert-scale question still yielded an above-average mean (M = 3.56, SD = 1.54). This suggests that despite the ban, students were still considering the use of AI. Additionally, the "No specific policy" condition recorded the highest mean AI Use score (M = 4.70, SD = 0.75), indicating that in the absence of a clear policy, AI use among students could be significantly high. Furthermore, the "Allowed and valued" policy showed the highest mean attitude towards AI (M = 4.30, SD = 1.12), suggesting that an open and supportive policy may foster a more positive attitude towards AI compared to other policies. A discrepancy is observed in the Expected Learning Outcomes, with the lowest mean recorded in the "No specific policy" condition (M = 3.32, SD = 1.24). This implies that clear guidelines regarding AI use may enhance students' expected learning outcomes.

Table 5.2:
Means and Standard Deviations of Study Variables by Policy

Variable	Allowed and valued		Allowed unless		No specific policy		Not allowed		Overall	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Algorithm Aversion	2.85	1.70	2.67	1.75	2.87	1.59	2.53	2.02	2.73	1.76
Trust in Human	4.88	0.99	4.57	1.14	4.50	1.04	4.41	1.27	4.59	1.12
Trust in AI	3.73	1.21	3.53	1.04	3.63	1.03	3.22	1.62	3.53	1.25
AI Use	4.33	1.08	4.37	1.03	4.70	0.75	3.56	1.54	4.23	1.21
Attitude towards AI	4.30	1.12	3.83	1.02	3.62	1.37	3.27	1.42	3.76	1.29
Expected Learning Outcomes	3.93	1.08	3.85	1.04	3.32	1.24	3.59	1.05	3.68	1.12

Note. This table presents the means and standard deviations for the study variables by policy condition. Participants (N = 125) were exposed to one of four different policy conditions.

5.2 Algorithm Aversion

5.2.1 H1a-b: Policies influence trust and attitudes

Linear regression results indicated that trust in AI (M = 3.53, SD = 1.25) was not significantly influenced by any of the policies. Consequently, these findings do not support H1a, indicating that the policies do not have a significant effect on Trust in AI. Therefore, the results suggest that no policy significantly impacts Trust in AI based on the current analysis.

However, the second model for Attitude towards AI (M = 3.76, SD = 1.29) showed a significantly negative effect ($\beta = -0.6798$, SE = 0.263, $p < 0.05$) for the "Not allowed" policy. This suggests that restrictive policies negatively impact attitudes towards AI.

Other significant factors influencing attitudes towards AI include Familiarity with AI ($\beta = -0.2021$, $p < 0.05$), indicating that greater familiarity with AI is associated with less positive attitudes. Trust in AI (Control) ($\beta = 0.2229$, $p < 0.01$) and Attitude towards AI Study ($\beta = 0.7666$, $p < 0.001$) were also significant predictors, suggesting that higher trust in AI and more positive attitudes towards AI studies are associated with more positive overall attitudes towards AI.

These findings partially support H1, indicating that while policies can influence attitudes toward AI, their impact on trust in AI is less clear.

5.2.2 H2a-b: Trust and Attitudes influence Algorithm Aversion

Linear regression results demonstrated that Trust in AI (M = 3.53, SD = 1.25) and Attitude towards AI (M = 3.76, SD = 1.29) significantly influence Algorithm Aversion. The regression coefficient for Trust in AI was marginally significant ($\beta = -0.5198$, SE = 0.315, $p < 0.10$), indicating that higher trust in AI is associated with lower algorithm aversion. Additionally, Attitude towards AI was a very significant predictor ($\beta = -0.6798$, SE = 0.263, $p < 0.05$), suggesting that more positive attitudes towards AI are associated with lower algorithm aversion.

5.2.3 H3: Policies influence Algorithm Aversion

Linear regression results demonstrated that only 1 policy significantly influence Algorithm Aversion. The "Not Allowed" policy was marginally significant ($\beta = -0.7698$, SE = 0.438, $p < 0.10$). This suggests that the 'Not Allowed' policy is associated with higher algorithm aversion compared to the baseline. Other significant factors include Attitude towards AI (Control) ($\beta = 0.5736$, SE = 0.208, $p < 0.01$) and Trust in AI (Control) ($\beta = 0.2807$, SE = 0.146, $p < 0.10$).

5.3 AI Use and Expected Learning Outcomes

5.3.1 H4: Algorithm Aversion influences AI Use

Linear regression results demonstrated that Algorithm Aversion significantly influences AI Use ($\beta = -0.5219$, SE = 0.081, $p < 0.001$). This result suggests that higher algorithm aversion is associated with decreased AI use.

Additionally, other factors were found to significantly influence AI Use. The "Not Allowed" policy showed a significant negative effect on AI Use ($\beta = -1.2857$, SE = 0.256, $p < 0.001$), indicating that restrictive policies significantly reduce AI use. Use of AI also significantly predicted AI Use ($\beta = 0.2016$, SE = 0.065, $p < 0.01$). Gender was also a significant factor ($\beta = -0.2741$, SE = 0.119, $p < 0.05$), suggesting that males have a higher AI use compared to females.

5.3.2 H5: AI Use influences Expected Learning Outcomes

Linear regression results demonstrated that AI Use significantly influences Expected Learning Outcomes ($\beta = 0.2855$, SE = 0.082, $p < 0.001$). This result suggests that individuals who are more inclined to use AI expect better expected learning outcomes.

Additionally, other factors were found to significantly influence Expected Learning Outcomes. Attitude towards AI (Control) was a significant positive predictor ($\beta = 0.4319$, SE = 0.121, $p < 0.001$), suggesting that more positive attitudes towards AI are associated with higher Expected learning outcomes. Trust in AI (Control) showed a marginally significant positive effect on Expected Learning Outcomes ($\beta = 0.1555$, SE = 0.083, $p < 0.10$), indicating that higher trust in AI is associated with better Expected learning outcomes. The "Allowed and Valued Policy" also had a significant negative effect on Expected Learning Outcomes ($\beta = -0.5851$, SE = 0.253, $p < 0.05$). .

5.3.3 H6: Policies influence AI Use

Linear regression results demonstrated that policies significantly influence AI Use. Specifically, the "Not Allowed" policy had a significant negative effect on AI Use ($\beta = -1.2857$, SE = 0.256, $p < 0.001$). This result suggests that restrictive policies that do not allow AI use are associated with a substantial decrease in AI use.

Furthermore, the "Allowed and Valued" policy also showed a significant negative effect on AI Use ($\beta = -0.5851$, SE = 0.253, $p < 0.05$). This indicates that even policies that allow and value AI use may negatively impact AI use compared to no specific policy.

Additionally, several control variables were found to significantly influence AI Use. Gender had a significant negative effect ($\beta = -0.2741$, SE = 0.119, $p < 0.05$), indicating that males tend to use AI more than females. The Use of AI variable was also significant ($\beta = 0.2016$, SE = 0.065, $p < 0.01$), suggesting that individuals who frequently use AI are more likely to continue using it. Algorithm Aversion had a significant negative effect on AI Use ($\beta = -0.5219$, SE = 0.081, $p < 0.001$), indicating that higher aversion to algorithms is associated with lower AI use.

Table 5.3:
Regression Results for Model 1-4

Variable	Model 1 Trust in AI	Model 2 Attitude towards AI	Model 3 Algorithm Aversion	Model 4 Algorithm Aversion
Intercept	2.4542***	0.9513	-2.0340*	-1.0833
	(0.690)	(0.576)	(0.955)	(0.959)
Age	0.1878†	-0.1203	0.1057	0.1090
	(0.111)	(0.093)	(0.150)	(0.155)
Gender	-0.2376	-0.2267†	0.0806	-0.0777
	(0.155)	(0.129)	(0.215)	(0.208)
Level of Education	-0.0877	0.0024	0.1362	0.1578
	(0.085)	(0.071)	(0.108)	(0.117)
Familiarity with AI	0.0152	-0.2021*	0.1394	-0.1704
	(0.104)	(0.087)	(0.138)	(0.145)
Use of AI	0.0988	0.0273	0.1487	0.1652
	(0.086)	(0.072)	(0.163)	(0.119)
Attitude towards AI (Control)	-0.0064	0.7666***	0.2500	0.5736**
	(0.150)	(0.125)	(0.221)	(0.208)
Trust in AI (Control)	0.3987***	0.2229**	0.0651	0.2807†
	(0.105)	(0.088)	(0.146)	(0.146)
Allowed and Valued Policy	-0.0626	0.4059	0.1039	-0.4585
	(0.311)	(0.260)	(0.221)	(0.398)
Allowed Unless Policy	-0.1180	0.1392	-0.0392	-0.3982
	(0.312)	(0.260)	(0.430)	(0.432)
Not Allowed Policy	-0.5198	-0.6798*	-0.0349	-0.7698†
	(0.315)	(0.263)	(0.420)	(0.438)
Trust in AI (Study)			0.2276†	
			(0.124)	
Attitude towards AI (Study)			0.4110**	
			(0.138)	
Observations	125	125	125	125
R-squared	0.207	0.474	0.288	0.218

Note. Standard errors are in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.10$

Table 5.4:
Regression Results for Model 5-7

Variable	Model 5 AI Use	Model 6 Learning Outcomes	Model 7 AI Use
Intercept	2.1835***	0.5190	2.5677***
	(0.529)	(0.587)	(0.560)
Age	0.0426	0.0244	-0.0139
	(0.085)	(0.088)	(0.090)
Gender	-0.2741*	-0.1250	-0.4065**
	(0.119)	(0.128)	(0.126)
Level of Education	-0.0408	0.0643	0.0325
	(0.062)	(0.065)	(0.069)
Familiarity with AI	0.0245	-0.1549	-0.0869
	(0.079)	(0.082)	(0.085)
Use of AI	0.2016**	-0.0215	0.1878**
	(0.065)	(0.070)	(0.070)
Attitude towards AI (Control)	-0.0978	0.4319***	0.3663**
	(0.126)	(0.121)	(0.121)
Algorithm Aversion	-0.5219***		
	(0.081)		
Trust in AI (Control)	-0.0135	0.1555†	0.1707†
	(0.080)	(0.083)	(0.085)
Allowed and Valued Policy			-0.5851*
			(0.253)
Allowed Unless Policy			-0.3358
			(0.253)
Not Allowed Policy			-1.2857***
			(0.256)
AI Use		0.2855***	
		(0.082)	
Observations	125	125	125
R-squared	0.505	0.354	0.434

Note. Standard errors are in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.10$

Chapter 6

Discussion

Table 6.1:
Empirical results

Hypotheses	Description	β	SE	p	Supported?
H1a	Policies influence Trust in AI	-0.5198	0.315	0.102	No
H1b	Policies influence Attitude towards AI	-0.6798*	0.263	0.011	Yes, Not Allowed
H2a	Trust in AI influences Algorithm Aversion	-0.1555†	0.083	0.062	Marginal
H2b	Attitude towards AI influences Algorithm Aversion	-0.5219***	0.081	< 0.001	Yes
H3	Policies influence Algorithm Aversion	-0.769†	0.438	0.081	Marginally
H4	Algorithm Aversion influences AI Use	0.5219***	0.081	< 0.001	Yes
H5	AI Use influences Expected Learning Outcomes	0.2855***	0.082	< 0.001	Yes
H6	Policies influence AI Use	-1.2857***	0.256	< 0.001	Yes, Not Allowed
		-0.5851*	0.253	< 0.05	Yes, Allowed and Valued

Note. Robust standard errors are in parentheses. ***p $<$ 0.001, **p $<$ 0.01, *p $<$ 0.05, †p $<$ 0.10

We aimed to address three research questions that explore the impact of university policies on algorithm aversion, students' attitudes towards AI, and their expected learning outcomes under different AI usage policies. The results are summarized in Table 6.1 and Section 5.1.

Our results show that students are on average quite familiar with several AI tools, see Figure 5.1. Moreover, students' general opinions of AI are quite hopeful and positive, see Figure 5.2. However they express their concerns about the exclusion and discrimination of AI and feel quite worried. Participants also have a positive attitude towards AI in general(Mean = 4.15 and SD = 0.94).

Our empirical results did not support Hypothesis H1a, which posited that universities' AI policies would influence participants' trust in AI. The relationship between policies and trust in AI was not significant ($\beta = -0.5198$, $p = 0.102$). This finding diverges from the theories proposed by Shin et al. (2020), who suggested that transparency, fairness, and accuracy in algorithmic services are critical for building user trust. Our results indicate that while university policies might shape other aspects of AI interaction, they do not directly influence trust in AI among students. However, it is important to note that we only provided students with an imaginary policy scenario Shin et al. (2020) and then instantly asked for their levels of trust. It is possible that more time and actual experience with learning at universities implementing such policies are necessary to change their trust due to the dual-process nature of heuristic and systematic processing. As Shin et al. (2020) discuss, heuristic processing involves quick judgments based on available information, whereas systematic processing requires more deliberate evaluation over time. Therefore, the immediate response in our study might not fully capture the potential long-term impact of well-implemented AI policies on trust.

Hypothesis H1b, which proposed that policies influence attitudes towards AI, is supported for the not allowed policy ($\beta = -0.6798$, $p = 0.011$), but not for other scenarios. This suggests that certain policy frameworks, particularly those that do not allow AI usage, can have a negative impact on attitudes towards AI. This is consistent with the notion that restrictive policies can foster negative perceptions and attitudes towards AI, as indicated by the negative beta value. Our findings partially align with the theories of Shin et al. (2020) and Chan (2023), who emphasized the importance of supportive policies in shaping positive attitudes towards AI.

Hypothesis H2a, which suggested that higher trust in AI would result in lower levels of algorithm aversion, showed marginal significance ($\beta = 0.2276$, $p = 0.069$). While this result is not strongly significant, it indicates a potential trend where increased trust in AI could reduce aversion. This finding partially supports the theories of Turel and Kalhan (2023), who proposed that implicit biases against AI drive algorithm aversion. However, the marginal significance suggests that trust may not be the only factor at play, highlighting the need for further research into additional factors. As noted by Jussupow et al. (2020), factors such as perceived capabilities and human involvement also influence whether users develop algorithm aversion. Moreover, Shin et al. (2020) discuss how trust is influenced by perceived transparency, fairness, accountability, and explainability (FATE). They found that these factors collectively influence trust, which in turn affects user satisfaction and the perceived usefulness of AI. Trust acts as a mediator between these algorithmic characteristics and user acceptance. Therefore, while trust may not directly influence algorithm aversion, it can have a significant mediating effect by interacting with other important factors.

Hypothesis H2b is supported ($\beta = -0.5219$, $p < 0.001$), indicating that participants with more positive attitudes towards AI exhibit lower levels of algorithm aversion. This finding aligns with the theories of Workman (2005), who found that people's perceptions and attitudes towards algorithms are strongly associated with algorithm aversion. Our results suggest that fostering positive attitudes towards AI can be an effective strategy to reduce algorithm aversion among students.

Hypothesis H3, which posited that university policies influence algorithm aversion, is marginally supported ($\beta = -0.769$, $p = 0.081$). This finding aligns with the theories proposed by Heßler et al. (2022), who suggest that the context of decision-making affects algorithm aversion. Specifically, they argue that contexts perceived as more personally relevant, such as prosocial decision-making, increase the perceived need for empathy and autonomy, which can heighten aversion to algorithms. This suggests that well-crafted AI policies in educational settings, which address the factors contributing to algorithm aversion, can help mitigate students' reluctance to engage with AI technologies. However, the marginal significance of these results indicates the need for more robust and targeted policy measures to effectively address algorithm aversion.

Hypothesis H4 is also supported ($\beta = -0.5219$, $p < 0.001$), indicating that algorithm aversion has a significant negative influence on the use of generative AI tools by students. This finding aligns with Dietvorst et al. (2015), who found that people tend to rely less on algorithms even when algorithms provide better decisions. Our results highlight the importance of addressing algorithm aversion to promote the effective use of AI tools in educational settings.

Hypothesis H5 is supported ($\beta = 0.2855$, $p < 0.001$), demonstrating that AI use positively influences expected learning outcomes. This finding corroborates the theories of Yilmaz and Yilmaz (2023), who suggested that AI can provide personalized and efficient learning assistance, thereby enhancing educational outcomes. Our results indicate that integrating AI tools into the educational experience can lead to improved learning outcomes for students.

Hypothesis H6 is supported for the not allowed policy ($\beta = -1.2857$, $p < 0.001$) and for the allowed and valued policy ($\beta = -0.5851$, $p < 0.05$), indicating that compared to the baseline of no specific policy, both restrictive policies and policies that explicitly allow and value AI usage are associated with lower AI use by students. These findings underscore the critical role of institutional policies in promoting or inhibiting the adoption and effective use of AI tools in education. This finding aligns with the theories of Chan (2023), who emphasized the importance of policies in shaping students' perceptions and usage of AI technologies. The negative impact of the allowed and valued policy compared to no specific policy highlights the nuanced effect of policy framing, indicating that more comprehensive strategies are needed to positively influence AI use among students. The negative coefficients suggest that compared to having no specific policy, implementing restrictive policies and even policies that explicitly allow and value AI usage can negatively impact AI use by students. This highlights that merely allowing and valuing AI is not sufficient; the manner in which these policies are framed and communicated is crucial. Supportive policies need to be effectively designed to address underlying concerns and barriers to AI adoption. Moreover, the presence of any policy (M = 4.70, SD = 0.75) makes students more deliberate in their use of AI. In the absence of a specific policy (the "wild west" scenario), students may use AI extensively to gain an advantage without considering potential guidelines or ethical implications. Therefore, having no policy at all can lead to unchecked and potentially problematic use of AI, while the presence of a policy, even if restrictive, prompts students to consider their AI use more carefully.

6.1 Research Implications

First, our findings suggest that university policies alone may not be sufficient to influence trust in AI, as indicated by the non-significant results for H1a. This diverges from previous theories by Shin et al. (2020), who emphasized transparency, fairness, and accuracy as critical for building user trust. However, our results imply that trust may develop over time through direct experience rather than immediate policy changes. This is somewhat aligned with Shin et al. (2020), who also argue that influencing trust in AI is a complex process that requires more than just policy implementation. Future research should therefore focus on a deeper exploration of the mechanisms through which trust in AI is built, considering the long-term effects of direct interaction with AI technologies.

Second, Hypothesis H1b shows that restrictive AI policies (not allowed) negatively influence attitudes towards AI. This supports the notion that restrictive policies can foster negative perceptions and hinder the adoption of AI technologies. This finding aligns with the theories of Shin et al. (2020) and Chan (2023), who emphasize the importance of supportive policies in shaping positive attitudes towards AI. Our study adds to the literature by providing empirical evidence that restrictive policies deter positive attitudes towards AI, suggesting that supportive and inclusive policies are crucial for promoting AI acceptance.

Third, Hypothesis H2a, which suggested a relationship between trust in AI and algorithm aversion, showed marginal significance. This partially supports the theories of Turel and Kalhan (2023), who proposed that implicit biases against AI contribute to algorithm aversion. Our study contributes to the literature by indicating that trust may not be the sole factor in reducing algorithm aversion. Instead, trust may interact with other factors such as perceived capabilities and human involvement, as noted by Jussupow et al. (2020), and the principles of FATE (Fairness, Accountability, Transparency, and Explainability), discussed by Shin et al. (2020). This highlights the complexity of algorithm aversion and the need for a multifaceted approach to addressing it.

Fourth, Hypothesis H2b demonstrates that positive attitudes towards AI are associated with lower levels of algorithm aversion, supporting Workman (2005). This finding contributes to the literature by confirming that fostering positive attitudes towards AI can be an effective strategy to reduce algorithm aversion. This underscores the importance of educational initiatives and policy frameworks that promote positive perceptions of AI.

Fifth, Hypothesis H3, marginally supported, indicates that well-crafted university policies can reduce algorithm aversion. This aligns with Jussupow et al. (2020)'s emphasis on the importance of transparency and fairness in algorithmic decision-making. Our study adds to the literature by suggesting that while university policies can influence algorithm aversion, the impact may be marginal, indicating the need for more comprehensive and robust policy measures.

Sixth, Hypothesis H4 confirms that algorithm aversion negatively impacts the use of generative AI tools by students, aligning with Dietvorst et al. (2015). This finding contributes to the literature by highlighting the critical role of addressing algorithm aversion to promote the effective use of AI tools in educational settings.

Seventh, Hypothesis H5 shows that AI use positively influences expected learning outcomes, supporting the findings of Yilmaz and Yilmaz (2023). This adds to the literature by providing empirical evidence that integrating AI tools in education can enhance learning experiences and outcomes for students.

Finally, Hypothesis H6, supported for both not allowed and allowed and valued policies, indicates that compared to the baseline of no specific policy, both restrictive and supportive policies are associated with lower AI use by students. This suggests that the mere presence of a policy prompts students to consider their AI use more carefully. This finding aligns with the theories of Chan (2023), who emphasized the importance of policies in shaping students' perceptions and usage of AI technologies. Our study adds to the literature by highlighting the nuanced impact of policy framing and communication on AI use, indicating that effective policy design is crucial for encouraging positive AI adoption.

In summary, our study contributes to the literature by challenging existing theories, providing empirical evidence on the impact of university policies on trust, attitudes, and algorithm aversion, and highlighting the complexity of these relationships. These insights underscore the need for comprehensive and multifaceted approaches to policy design and implementation to foster positive AI adoption and usage in educational settings.

6.2 Practical Implications

The findings suggest that simply having a policy in place is not enough to foster positive attitudes and trust in AI. Policies must be thoughtfully designed and communicated to address students' concerns and barriers to adoption. Institutions should focus on creating policies that emphasize transparency, fairness, accountability, and explainability (FATE) principles to build trust over time, as suggested by Shin et al. (2020).

Our results indicate that influencing students' trust in AI through policy alone is challenging. Initial trust levels have a significant impact on their overall trust in AI, making it difficult to alter these perceptions solely through policy changes. Policymakers should consider this when designing AI-related policies, recognizing that trust may develop more effectively through direct and positive interactions with AI technologies over time.

In contrast, attitudes towards AI appear to be more easily influenced by policy. Restrictive policies that do not allow AI usage can foster negative attitudes and influence students' use of AI. Conversely, promotive and valued policies can make students more deliberate in their use of AI. Compared to having no policy at all, these policies result in students being less inclined to use AI indiscriminately, indicating that they consider the purpose of their AI use more carefully. Such policies are crucial for fostering a positive perception of AI, which is essential for its acceptance and effective use.

Moreover, universities should consider the implications of having no specific policy in place. In such scenarios, students may use AI extensively, which can benefit some but create unfair disadvantages for those who prefer to avoid AI usage. This lack of regulation can lead to inequities among students, underscoring the need for clear and fair AI policies. Researchers and policy experts unanimously recognize the necessity of these policies. For instance, administrators highlight the importance of safeguarding student safety and mitigating plagiarism risks (Ghimire & Edwards, 2024).

The study shows that how policies are framed and communicated significantly impacts AI use. Institutions should ensure that their AI policies are clearly communicated and that students understand the guidelines and benefits. Effective communication can help in addressing misconceptions and promoting a deliberate and responsible use of AI technologies. Additionally, educational initiatives are crucial in shaping positive attitudes towards AI. Institutions should develop programs and workshops that educate students about the benefits, limitations, and ethical considerations of AI, which can help reduce algorithm aversion by fostering a better understanding and appreciation of AI technologies. We provide empirical evidence in line with Chan (2023), supporting the importance of policy framing, communication, and educational initiatives.

Additionally, policies should ensure transparency, accountability, and inclusivity, addressing biases and ensuring equitable access to AI technologies (UNESCO, 2021). Our participants expressed concerns about the exclusivity and potential discriminatory impacts of AI, highlighting the need for policies that address these worries.

By focusing on these practical implications, institutions can create a supportive environment that encourages the effective use of AI technologies, ultimately leading to enhanced learning outcomes and better preparation of students for a future where AI plays a significant role.

6.2.1 Limitations and Future Research

Several limitations that point to future research opportunities are noteworthy. First, the study was conducted with a relatively small sample size (n = 156), which may limit the generalizability of our findings. Future research should aim to include a larger and more diverse sample to enhance the robustness of the results. Moreover, the data collection was carried out through social media channels and the authors' own network, which might introduce selection bias and limit the representativeness of the sample. It is important for future studies to utilize a broader range of data collection methods to ensure a more representative sample.

Secondly, we only examined the policies of Dutch universities. This geographical focus may not reflect the policy impacts in other regions or countries. Further studies should explore the effects of AI policies in a variety of educational contexts to enhance generalizability.

Third, the study measured the effects of policies at a single point in time. Understanding the long-term impact of AI policies requires longitudinal studies that can capture changes over time. This would provide a more comprehensive view of how policies influence trust, attitudes, and AI usage. Shin et al. (2020) suggests that trust in AI is influenced by a complex interplay of factors, which may develop more fully over an extended period. To truly measure the impact on trust, it is necessary to consider additional variables and observe how they interact over time.

Fourth, our study primarily used quantitative measures. Including more qualitative questions in future research could provide deeper insights into students' perceptions and attitudes towards AI. This would help in understanding the nuances of their experiences and the reasons behind their responses. Qualitative data can uncover underlying factors and provide a richer context for the quantitative findings, bridging the gap between statistical correlations and real-world applications.

Fifth, the study provided hypothetical policy scenarios to participants. Examining the effects of actual implemented policies would yield more accurate and practical insights. Future research should focus on real-world policy implementations and their impacts.

Addressing these limitations in future research could enhance the robustness and applicability of the findings, providing a more comprehensive understanding of the impact of AI policies in educational settings.

Chapter 7

Conclusion

In this study, we explored students' attitudes towards AI in education, focusing on how university AI policies impact trust, algorithm aversion, and expected learning outcomes. Our findings reveal that students generally have positive attitudes towards AI and recognize its benefits, though they express concerns about bias and over-reliance. The results from our empirical research indicate that while policies do not directly influence students' trust in AI, restrictive policies prohibiting AI usage lead to a slight change in attitudes. Moreover, students tend to utilize AI tools more frequently when specific policies are absent. This highlights the significant role that well-designed AI policies play in shaping how AI is used in educational settings.These results emphasize the importance of designing AI policies that foster transparency, fairness, and ethical use to optimize educational outcomes. Future research should consider a broader range of educational settings and employ longitudinal approaches to better understand the long-term effects of AI policy integration. Our study contributes to the ongoing discourse on AI in education, highlighting that thoughtful and effective policy design is essential for maximizing the educational benefits of AI while mitigating potential risks. As AI increasingly becomes an integral component of the education system, it is crucial to engage with students and establish transparent policies that they are willing to embrace, thereby ensuring that rulebook becomes reality.

Appendix A

Survey

Part 0: Introduction

Welcome to the research study!

We are interested in understanding the influence of universities' AI policies on algorithm aversion. In this study, you will be presented with information about a hypothetical university's AI policy. After reviewing the information, you will be asked to answer some questions regarding your thoughts and opinions. Your responses will be kept completely confidential.

The study should take you around 5 minutes to complete. Your participation in this research is voluntary. You have the right to withdraw at any point during the study. The Principal Investigator of this study can be contacted at d.fidder@tilburguniversity.edu

By clicking the button below, you acknowledge:

- Your participation in the study is voluntary.
- You are 18 years of age.
- You are aware that you may choose to terminate your participation at any time for any reason.

Options:

- I consent, begin the study
- I do not consent, I do not wish to participate

Part 1: Control Variables (Demographic and Background Information)

Age

How old are you?

- Under 18
- 18-24 years old

- 25-34 years old
- 35-44 years old
- 45-54 years old
- 55-64 years old
- 65+ years old

Gender
How do you describe yourself?

- Male
- Female
- Non-binary / third gender
- Prefer to self-describe: ______
- Prefer not to say

Level of Education
What is the highest level of education you have completed?

- Some primary school
- Completed primary
- Some Secondary school
- Completed secondary school
- Vocational or Similar
- Some university but no degree
- University Bachelors Degree
- Graduate or professional degree (MA, MS, MBA, PhD, JD, MD, DDS etc.)
- Prefer not to say

Primary Field of Education
What is your primary field of education? (Select all that apply)

- Engineering and Technology
- Health and Medical Sciences
- Economics and Business

- Humanities
- Social Sciences
- Natural Sciences
- Law
- Arts and Design
- Environmental Sciences
- Education
- Other (Please specify): ______
- Prefer not to say

Part 2: Use of AI-Based Tools for Studying (Control Variables)

Familiarity with AI Concept
To what extent are you familiar with the general AI concept?

- Not at all familiar
- Slightly familiar
- Somewhat familiar
- Moderately familiar
- Very familiar
- Extremely familiar
- Completely familiar

Frequency of AI Tool Usage
How often do you use AI-based tools for studying?

- Not at all
- Very Rarely
- Rarely
- Sometimes
- Often
- Very Often

- Always

Experience with AI Tools
Rate your experience with the following AI tools:
Text-generating AI (e.g., ChatGPT)

- Not familiar at all
- Slightly familiar
- Somewhat familiar
- Moderately familiar
- Very familiar
- Extremely familiar
- Completely familiar

Presentation-generating AI (e.g., TOME)

- Not familiar at all
- Slightly familiar
- Somewhat familiar
- Moderately familiar
- Very familiar
- Extremely familiar
- Completely familiar

Image-generating AI (e.g., Dall-E 2)

- Not familiar at all
- Slightly familiar
- Somewhat familiar
- Moderately familiar
- Very familiar
- Extremely familiar
- Completely familiar

Translation AI (e.g., DeepL)

- Not familiar at all
- Slightly familiar
- Somewhat familiar
- Moderately familiar
- Very familiar
- Extremely familiar
- Completely familiar

Other AI Tools Used
If you used other AI tools, please state here (Optional):
______
General Attitude Towards AI
Based on your experience and/or familiarity with artificial intelligence (AI), please indicate the extent to which you agree with the following statements:
Using AI is a good idea.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neutral
- Somewhat Agree
- Agree
- Strongly Agree

Using AI is a wise idea.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neutral
- Somewhat Agree
- Agree
- Strongly Agree

Using AI is a desirable thing.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neutral
- Somewhat Agree
- Agree
- Strongly Agree

Using AI is beneficial.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neutral
- Somewhat Agree
- Agree
- Strongly Agree

Even if not fully understood, I'd trust artificial intelligence tools to do a good job.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neutral
- Somewhat Agree
- Agree
- Strongly Agree

I trust artificial intelligence tools.

- Strongly Disagree

- Disagree
- Somewhat Disagree
- Neutral
- Somewhat Agree
- Agree
- Strongly Agree

Artificial intelligence tools are trustworthy.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neutral
- Somewhat Agree
- Agree
- Strongly Agree

Part 3: AI Aversion Measurement with Policy Scenarios

Policy Introduction

You will now review a hypothetical university policy on using AI tools like ChatGPT in assignments and exams. Each scenario describes a fictional university's approach to AI tool usage. You will receive one scenario to consider. After reading, please answer the questions based on the described policy. Your honest responses will help us understand the impact of different AI policies in education.

Support Preference

Imagine you are working on an assignment and have the option to choose between two types of support: a human supporter or a computerized decision support system (e.g., AI tools like ChatGPT)

Who would you choose to help you with your academic assignments?

- Definitely Human Support
- Prefer Human Support
- Slightly Prefer Human Support
- Neutral

- Slightly Prefer AI Support
- Prefer AI Support
- Definitely AI Support

Trust in Support Systems
To what extent do you trust a human to support you in your academic work?

- Not at all
- Very little
- Slightly
- Neutral
- Moderately
- Quite a bit
- Very much so

To what extent do you trust AI to support you in your decision?

- Not at all
- Very little
- Slightly
- Neutral
- Moderately
- Quite a bit
- Very much so

AI Policy Impact on Study Habits
Under the given policy...
I would use AI-based tools for studying

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

- Agree
- Strongly agree

Using AI is a good idea

- Strongly Disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Using AI is a wise idea

- Strongly Disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Using AI is a desirable thing

- Strongly Disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Using AI is beneficial

- Strongly Disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Perceived Learning Outcomes
Under this policy, I believe AI tools will...
Improve my ability to come up with innovative solutions to problems

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Improve my ability to break down complex problems into manageable steps

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Improve my ability to collaborate effectively with my peers

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Improve my ability to analyze and evaluate information systematically

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Improve my ability to generate multiple solutions to a given problem

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Part 4: Optional Section - General Opinions and Attitudes Towards AI

Survey Continuation

Thank you for completing the main part of our survey! We now have a few additional questions regarding your general opinions and attitudes towards AI. This section is completely optional, but your responses will provide valuable insights into broader perceptions of AI and help us immensely in understanding the diverse viewpoints on AI.

Would you like to continue to this optional section?

- Yes, I would like to continue
- No, I would like to finish the survey

Feelings About AI Potential

The potential and possible further developments of AI and AI-based tools make me feel...

- Uneasy
- Somewhat Uneasy
- Neutral
- Somewhat Hopeful
- Hopeful
- Neither

Perceived Benefits vs. Drawbacks of AI

With regard to the benefits of AI and AI-based tools, in my view what outweighs are in general the...

- Disadvantages
- Somewhat Disadvantages
- Neutral
- Somewhat Advantages
- Advantages
- Neither

Impact of AI on Global Challenges

Regarding the degree of impact of AI-based tools on global challenges such as climate change, poverty or hard-to-cure diseases, I am...

- Pessimistic

- Somewhat Pessimistic
- Neutral
- Somewhat Optimistic
- Optimistic
- Neither

General Sentiment on AI Development
In general, regarding the development and increasing use of AI and AI-based tools I am...

- Averse
- Somewhat Averse
- Neutral
- Somewhat Approving
- Approving
- Neither

Concerns About AI and Discrimination
Regarding the impact of AI-based tools on exclusion and discrimination, I am...

- Worried
- Somewhat Worried
- Neutral
- Somewhat Confident
- Confident
- Neither

Appendix B

AI Policies Scenarios

Scenario 1: Strict Usage Policy ("Explicit Permission Required")

Name: Northern Plains University

At Northern Plains University, the use of AI tools like ChatGPT for written assignments is considered cheating unless explicitly mentioned otherwise. If students use AI for assignments without proper citation or the instructor's explicit permission, it is deemed academic dishonesty. Any use of AI that prevents the teacher from assessing the student's original work is not allowed. During exams or other evaluations, AI use is prohibited unless specifically indicated as allowed. The university offers resources and support for students to learn how to use AI tools effectively.

- **Not allowed:**
  - Any form of copying AI-generated content without full attribution.
  - Any use of AI that hinders the teacher's ability to evaluate the student's work.
  - Any use of AI during exams unless explicitly permitted.

Scenario 2: Flexible Usage Policy ("Instructor Discretion")

Name: East River College

At East River College, the use of AI tools is allowed unless otherwise specified by the course instructor. Students are encouraged to consult their instructors about the acceptable use of AI in their assignments. The university provides general guidelines for responsible AI usage and expects students to follow the specific policies set by their instructors. The university offers resources and support for students to learn how to use AI tools effectively.

- **Allowed unless otherwise specified:**
  - Use of AI tools is permitted, but students must check with their instructors for specific course policies.

- Students should provide proper citations when using AI-generated content.
- Instructors have the discretion to set additional rules regarding AI use in their courses.

Scenario 3: Encouraged Usage Policy ("AI Integration and Value")

Name: Westbrook Institute of Technology

At Westbrook Institute of Technology, the use of AI tools like ChatGPT is actively encouraged as part of the learning process. The university sees significant value in integrating AI into education to enhance learning outcomes. Students are encouraged to explore AI tools and incorporate them into their studies, provided they do so ethically and with proper citation. The university offers resources and support for students to learn how to use AI tools effectively.

- **Allowed and valued:**
  - AI tools are encouraged to enhance learning and academic performance.
  - Students should use AI ethically and provide proper attribution for AI-generated content.
  - The university offers resources and support for students to learn how to use AI tools effectively.

Scenario 4: Baseline Policy ("No Specific Policy")

Name: Southern Lakes University

At Southern Lakes University, there are no specific policies or guidelines regarding the use of AI tools like ChatGPT in assignments. Students are left to their discretion on whether and how to use AI tools in their academic work. The university does not provide explicit rules, leaving the decision to individual students and their judgment. The university offers resources and support for students to learn how to use AI tools effectively.

- **No specific policy:**
  - No official guidelines on the use of AI tools in assignments.
  - Students are responsible for using AI tools ethically and ensuring academic integrity.
  - The university offers resources and support for students to learn how to use AI tools effectively.

Appendix C

Use of AI Tools and Other Digital Resources

Appendix C: Use of AI Tools and Other Digital Resources

In the development of this thesis, several AI tools and digital resources were employed to enhance the quality and efficiency of our work. Below, we provide a detailed account of the tools used, specifying their application and ensuring transparency in our use of these technologies.

1. ChatGPT

We utilized ChatGPT as a co-creator throughout various stages of our thesis. Its applications included:

- **Proofreading:** ChatGPT assisted in identifying grammatical errors and improving the overall readability of our text.
- **Improving Text Quality:** ChatGPT was used to enhance the quality of the text across all chapters, focusing on clarity and coherence.
- **Mindmapping:** We used ChatGPT to brainstorm and organize ideas effectively.
- **Summarizing Background:** ChatGPT helped in summarizing research papers and relevant literature in the Background section.
- **Qualitative Data Interpretation:** As detailed in the Methods section, ChatGPT assisted in interpreting qualitative data.
- **Creating and Modifying Visualizations:** ChatGPT aided in creating and adjusting visualizations for the report, including LaTeX tables and other graphical representations.

2. Preplixity and Litmaps

- **Mindmapping:** Preplixity and Litmaps were instrumental in visualizing complex relationships among concepts and structuring our research findings.

3. Co-pilot

- **Writing and Debugging Code:** Co-pilot aided in writing and debugging code snippets that were integral to our research.

4. SciT

- **Finding Contradictions:** SciT was used to identify contradictions within the literature.

Throughout the use of these tools, we adhered to the following principles:

- **Originality:** We ensured that all work produced remained original and was not merely copied from tool-generated outputs. We did not use "ctrl+c" and "ctrl+v" to transfer text directly from these tools into our thesis.
- **Critical Assessment:** Every piece of content generated or suggested by these tools was critically evaluated and revised to ensure accuracy, relevance, and alignment with our research objectives.
- **Transparency:** In compliance with university policies, we have clearly indicated where and how these tools were used. Specific sections of our thesis where these tools were applied are detailed in the reference table below.

Table C.1: Details of AI Tool Usage
Chapter and Tool Applications

Chapter/Section	Tool Used	Specific Application
Introduction	ChatGPT	Proofreading, improving text quality
Background	ChatGPT	Summarizing research papers and relevant literature
Hypothesis	ChatGPT	Improving text quality
Methods	ChatGPT	Qualitative data interpretation
Results	Co-pilot	Writing and debugging of code used for data analysis
Discussion	ChatGPT	Creating and modifying visualizations, including LaTeX tables
Conclusion	ChatGPT	Proofreading, improving text quality

Note. This table details the use of AI tools throughout various chapters of the thesis, specifying the applications of each tool.

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