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UNIVERSITY STUDENTS' AWARENESS AND BEHAVIOURAL INTENTIONS
TOWARDS SUSTAINABLE AI ENGAGEMENT

Bachelor's Thesis
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I have written this Bachelor's Thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

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Introduction

Artificial intelligence (AI) has become an integral part of today's society, its influence spans across multiple industries and is widely recognised for its potential to address sustainability challenges, such as optimising energy efficiency and resource management (Tanveer et al., 2020). Unfortunately, AI's rapid advancements also raise significant environmental concerns, including but not limited to its high energy consumption and reliance on non-renewable resources (Yu et al., 2024; Strubell et al., 2020). These limitations highlight the dual role that AI plays, as both a solution and contributor to sustainability challenges, and emphasises the importance of understanding the factors that influence its responsible development and use.

University students, as future professionals and decision makers are well positioned to shape the future of AI's sustainability development. Kirby and Zwickle (2021) observed that university students demonstrated stronger levels of sustainability behaviours, higher attitudes and greater knowledge than the general public. This suggests that universities may play a large role due to the structured environment they provide for their students. Universities can also foster these factors through targeted educational programs and initiatives. However, students may present strong sustainability values in general, but little is known about how these values translate into behavioural intention regarding technologies like AI. As the topic of AI is complex and relatively new, students may find it challenging to act on their knowledge and values. Understanding how students engage with sustainability, in the context of AI, is crucial to bridge the gap between awareness and intentional behaviour.

This thesis aims to find out how university students' awareness of the environmental impact of AI influences their intentions to engage in sustainable AI practices. The research tasks designed to achieve this aim include:

- Defining and contextualising the use and environmental impact of AI within the academic setting and explaining its relevance to university students' sustainability behaviour through the framework of the Theory of Planned Behaviour (TPB).
- Examining existing research on university students' sustainability behaviours and highlighting key findings on awareness, attitudes, subjective norms, perceived behavioural control and socio-demographic factors.
- Developing and applying a conceptual framework based on the TPB, positioning awareness as a precursor to students' intention to engage in sustainable AI practices.

- Interpreting the results of the empirical study through the lens of the TPB and discussing their implications for promoting sustainable AI practices among university students.

This thesis consists of two main chapters. Chapter 1 presents the theoretical foundation by defining and contextualising the environmental impact of AI in the context of sustainability, in relation to university students. Additionally, the chapter presents the conceptual framework used in this thesis, positioning awareness as a precursor to students' intention to engage with AI in a sustainable manner. The chapter concludes by reviewing existing research on students' sustainability behaviour, with a focus on the key constructs of the TPB. Chapter 2 presents the methodological approach and empirical analysis. It outlines the questionnaire development, sampling strategy and statistical methods used to analyse the relationships between TPB variables. The findings are analysed using descriptive statistics, mean comparisons, subgroup analysis, correlation and regression. The chapter concludes with a discussion of the results compared to previous empirical studies and provides implications for promoting sustainable AI practices among university students.

Keywords: AI, environmental awareness, behavioural intention, university students, Theory of Planned Behaviour

1. Theoretical framework on university students' sustainable engagement with AI

1.1 Conceptualising AI's environmental impact and the role of student awareness and behaviour

In the following subchapter, the author will explore the role of AI in university settings, examining its widespread academic use and its overlooked environmental costs. Outlining how students engage with AI tools and what motivates their use and shifting towards the environmental implication of AI development and infrastructure. Lastly, the author will introduce the TPB as a guiding framework to examine how the TPB constructs and awareness influence students' intention to adopt more sustainable AI practices.

AI has evolved over the decades, starting with symbolic reasoning models in the 1950s and advancing through neural networks and modern deep learning applications (Emmert-Streib et al., 2020). Despite the widespread use of AI, defining it remains a challenge due to its broad and interdisciplinary nature, however AI generally refers to a system's ability to mimic human cognitive functions such as learning, decision making and problem solving where its applications span many diverse fields (Zhuk, 2023).

In the educational context, AI powered systems, such as adaptive learning tools and tutoring platforms, enhance students' ability to effectively manage their learning processes and solve complex problems (Fošner, 2024). Baillifard et al. (2023) found that AI tutoring systems utilising personalised learning techniques, including adaptive retrieval practice and dynamic neural network models, showed a significant improvement in students' academic performance. This indicates that the integration of AI into university students' daily lives is a growing trend as it creates an opportunity to prepare them for future academic and professional success.

The widespread usage of AI tools like ChatGPT is currently reshaping how university students engage with academic tasks. Which creates increased interest regarding the way these tools are used in higher education. Recent studies show that university students commonly use ChatGPT for tasks such as writing support, summarising texts, generating ideas and solving academic problems (Shuhaiber et al., 2025; Strzelecki, 2024; Faraon et al., 2025). The overview of the studies discussed can be seen in Table 1. These types of applications suggest that AI tools, such as ChatGPT, are not only supplementary tool's but rather an integral part of many university students' study routines. While students value these tools for its effectiveness and convenience, especially in managing time intensive assignments, many contextual and psychological factors influence the reasons behind its use.

Table 1

Overview of student's use of AI and key motivating factors

Author(s) & Year	Region	Common academic uses of AI	Main factors influencing AI use
Shuhaiber et al. (2025)	UAE	Writing assignments, idea generation, learning complex topics and receiving explanations	Usefulness, ease of use, enjoyment and trust in the tool's reliability
Strzelecki (2024)	Poland	Generating text, summarising information, solving academic problems and writing support	To improve academic performance, higher influence among master's students than bachelor's students
Faron et al. (2025)	Nordic countries & USA	Summarising texts, generating ideas, answering questions and assistance with assignments	Habit, usefulness and enjoyment; social pressure more relevant in the U.S.

Source: Compiled by author based on the sources presented in the table

Shuhaiber et al. (2025), Strzelecki (2024) and Faraon et al. (2025) all found that performance expectancy emerged as one of the key predictors of students' intention to use ChatGPT. However, the influence of other factors varied between the study regions. Strzelecki (2024) found that master's students were more influenced by performance outcomes than bachelor students. While Shuhaiber et al. (2025) highlighted the role of enjoyment and trust in the tool alongside performance expectancy in shaping students' motivation to use ChatGPT. On the other hand, Faron et al. (2025) identified regional differences, with social pressure and personal innovativeness being more important in the U.S. than in the Nordic countries. These findings illustrate that while ChatGPT is widely used, the motivations behind its use are shaped by academic level, cultural context and personal attitudes.

At the same time, concerns about excessive reliance on AI and academic integrity still exist, indicating a conflict between ethical considerations and perceived benefits (Strzelecki, 2024; Shuhaiber et al., 2025). In the context of this thesis, it is important to understand what students use AI for and why they choose to use it. This helps examine how these usage patterns relate to students' awareness of AI's environmental impact and their attitudes towards sustainable AI practices.

Moreover, students are not only consumers but additionally potential developers of AI technologies and their awareness and attitudes towards AI play a critical role in deciding how

these tools are adopted and used responsibly (Wang & Li, 2024). Understanding students' engagement with AI provides insights into their behaviour towards its environmental implication, particularly the dominant challenges posed by high energy consumption and reliance on non-renewable resources (Chakraborty, 2024).

The rapid growth of AI, across various fields, has led to rising computational demands that pose significant environmental costs and require additional scrutiny (Thompson et al., 2020). Yu et al. (2024) also highlight the required significant computational power in the various systems, specifically during the training and inference stages, which contribute noticeably to the global carbon emission. Furthermore, Strubell et al. (2020) reveal that training a single large model, can emit CO₂ equivalent to a lifetime emissions of five petrol powered cars. Although these numbers might seem arbitrary, they highlight a more significant structural problem, that the advancement of AI is not nearly as sustainable as it is often perceived.

The infrastructure supporting AI is the basis for its energy intensive nature, as data centres are one of the main contributors to its environmental impact, powered predominantly by fossil fuels (Chakraborty, 2024). Chakraborty (2024) also points out that despite the advancements in multiple renewable energy integrations, coal and natural gas still remain the dominant sources and perpetuate the carbon footprint of AI. Wu et al. (2024) add to this discussion by emphasising lifecycle emissions, which revealed that embodied carbon emission from manufacturing AI hardware accounts for 30-50% of total lifecycle emission, while operational energy use during training and inference contributes to the rest of the carbon footprint. These findings reveal a hidden layer to the environmental costs often overlooked when discussing AI.

While these statistics paint a concerning image, it is essential to critically reflect on what these challenges mean for a broader narrative of sustainability. Pachot and Patissier (2023) address the inherent paradox in AI's dual role, as AI holds immense potential to optimise energy usage and address multiple environmental challenges and on the other hand, its own operations undermine these very goals through high energy demands and reliance on non-renewable energy. To achieve true sustainability in AI it necessitates the development of energy efficient algorithms, increased reliance on renewable energy sources to power the data centres and the integration of environmental impact assessments into AI development (Pachot & Patissier, 2023).

These environmental implications are notably relevant to university students as they represent a critical group of both users and potential developers of AI. Their awareness and

attitudes toward AI's sustainability challenges can change how these systems are adopted in the future. More deliberate and sustainable use of AI may result from enabling students to evaluate the trade-offs of emerging technologies. The need for awareness extends beyond understanding energy consumption statistics and rather it involves the ability to recognise how individual behaviour can mitigate the environmental costs of AI.

The TPB is one of the most reliable and widely used models to understand pro-environmental behaviour (Tian & Liu. 2022). A meta-analysis by Hagggar and Hamilton (2024) revealed that TPB's main constructs, attitude, subjective norms and perceived behavioural control (PBC), were still strong predictors of both people's behavioural intentions and their actual behaviour over time. One of the main strengths of TPB is how it connects people's beliefs with their behavioural intentions (Hagger & Hamilton. 2024), making it applicable for studying behaviours related to sustainability. This reliability across different behaviours and contexts also supports TPB's use as a base model for more customised approaches, where researchers adapt it to their specific topic. As a result, many studies have introduced additional variables to understand the particular behaviour being studied. Yadav and Pathak (2016) found that by adding environmental concern and awareness to TPB, it made the model more effective in explaining young people's intentions to buy green products. Rather than using a different model, these kinds of extensions build on TPB's core strengths and allow researchers to account for the complexity of real-world human behaviour. As such, TPB remains a stable and coherent framework to study a wide range of behaviours.

Furthermore, TPB has been tested as part of larger integrated models. Klöckner (2013) combined TPB with other theories in their meta-analysis and found that intention and PBC, variables from TPB, along with habits were the strongest predictors of environmental behaviour. This indicates that the TPB variables remained relevant across the many different studies. While models like the Value Belief Norm theory and Norm Activation Model emphasise moral obligation and personal norms as the main factor of behaviour, TPB focuses on behavioural intention and perceived control (Klöckner. 2013). Additionally, integrating moral norms into TPB based models can enhance the predictive power, particularly in the context of pro-environmental behaviour (Bamberg & Möser, 2007). While this research does not explicitly include moral norms, their relevance further demonstrates TPB's models' ability to adapt to context specific circumstances.

Han (2015) and Chen (2016) illustrate how TPB applies to environmental contexts, specifically how awareness of environmental issues strengthens moral obligations and

positive attitudes toward sustainable behaviours. Han (2015) found that awareness of sustainability values influenced pro-environmental lodging choices, while Chen (2016) discovered that understanding the impact of climate change encouraged individuals to adopt energy saving practices. These two studies highlight a recurring pattern, awareness serves as a foundation, but additional factors are necessary to bridge the gap between intentions and behaviour. Please see Figure 1 for the conceptual model of the TPB.

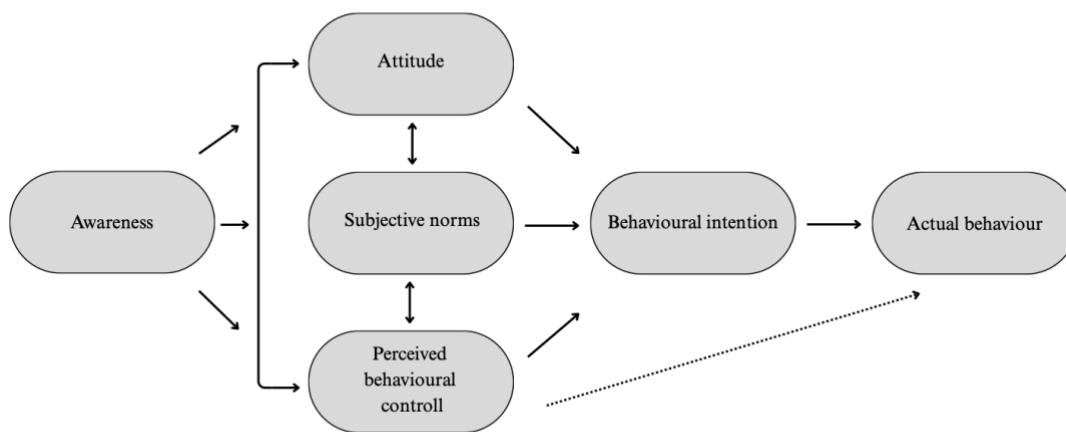


Figure 1 : Conceptual model of the TPB

Note: Lines show direct effect and dotted line shows indirect effect; Awareness is not a part of the original model and was added by the author

Source: Compiled by the author based on Ajzen's (1991)

However, it is not always straightforward. Kollmuss and Agyeman (2002) highlight the persistent gap between awareness and action, attributing it to challenges such as perceived inefficiency or external limitations like infrastructure. This viewpoint is specifically relevant in the context of AI, as the environmental costs of high energy consumption may seem abstract or beyond an individual's control. Yuriev et al. (2018) argue that overcoming such challenges often require a supportive environment, such as workplaces, communities or educational settings. This understanding provides another critical point that fostering sustainable behaviours is not only an individual's effort but a collective one, where social norms and institutional frameworks definitely play an influential role.

In the context of AI, the interplay between awareness and behaviour becomes even more nuanced. Wang et al. (2016) showcase how awareness of a technology's environmental impact can shape attitudes and adoption intentions. However, Chen (2016) argues that

awareness alone is insufficient without a sense of moral obligation and perceived control. These findings are also significantly important for university students, as mentioned before that they can be both users and potential developers of AI. Encouraging critical reflection on the sustainability challenges of AI can help students view their role in addressing these issues, energy demands and carbon footprint.

Thus, TPB provides a structured framework through which to examine these dynamics, but it also creates the opportunity for further reflection. Awareness and attitudes are not fixed, they can be shaped by context, experiences and the availability of alternatives. Through critical examination of the factors that influence behavioural intention, we can better understand the conditions under which awareness translates into meaningful action.

In this subchapter, the author outlined how university students engage with AI tools and examined the environmental implications of AI through the lens of TPB. The literature review confirmed that AI use is widespread in academic contexts, mainly driven by usefulness, efficiency and performance expectations. However, motivations vary across academic levels and regions, showing the influence of context specific and social factors.

Additionally, the author demonstrated that awareness, not part of the original TPB, plays a vital role in shaping behavioural intentions. This is supported by extensions of the model that include awareness factors, specifically in sustainability-related fields.

Lastly, by bringing to light the environmental costs of AI infrastructure and data processing, the author underscores the need for greater student awareness and institutional support. The TPB provides a useful foundation for exploring how awareness, attitudes, social norms and PBC interact to influence students' intention towards more sustainable AI use.

1.2. Overview of empirical research on TPB constructs and student pro-environmental behaviour

In this subchapter, the author examines key empirical studies that explore the relationship between awareness, attitudes, subjective norms, PBC and behavioural intentions within the framework of the TPB. The reviewed studies focus on environmentally sustainable behaviours among university students, as research on sustainable AI behaviour is currently limited. Nevertheless, these studies provide relevant insights into how the key TPB constructs interact in environmental contexts. In particular, they highlight potential pathways through which awareness influences behaviour and how sociodemographic factors may affect these relationships. All of the discussed studies can be found in Table 2.

Table 2

Summary of TPB studies on student pro-environmental behaviour

Authors & Year	Sample & Country	Key TPB Constructs	Key findings
Wu et al. (2022)	N = 434, China	Attitude, SN, PBC, personal norms, knowledge	Awareness directly and indirectly predicts behaviour; attitudes not significant.
Phang & Ilham (2023)	N = 394, Malaysia	Attitude, SN, PBC	Attitudes, SN and PBC predict intentions; PBC doesn't predict actual behaviour directly.
Tikir & Lehmann (2011)	N = 3541, Switzerland	Attitude, SN, PBC, cultural values	Attitudes strongest predictor of intention, followed by SN-s; cultural values indirectly influence intentions.
Tsai & Tan (2022)	N = 133, Taiwan	Attitude, SN, PBC, moral norms	PBC strongest predictor of intention, followed by attitudes and SN-s; moral norms predict SN-s and PBC.
Correia et al. (2022)	N = , Portugal	Attitude, SN, PBC, knowledge	SN-s and PBC predict intention and behaviour; attitudes and knowledge insignificant.
Macovei (2015)	N = 133, Romania	Attitude, SN, PBC, Awareness	Awareness, attitudes, SN-s, and PBC predict intentions; intentions predict actual behaviour.

Note: SN = Subjective norms.

Source: Compiled by author based on the sources presented in the table

Wu et al. (2022) conducted a study on waste management behaviour among Chinese university students. Their findings showed that environmental knowledge directly predicted students' waste management behaviour. Additionally, environmental knowledge also indirectly influenced behaviour through environmental concern, personal norms and PBC. These findings highlight that knowledge, or in other words awareness, can have both direct and mediated effects on behaviour. This also suggests that informational interventions may be effective when combined with strategies that strengthen norms and perceived control.

Similarly, Phang and Ilham (2023) found that environmental attitudes and subjective norms significantly influenced pro-environmental intentions. Additionally, PBC significantly predicted behavioural intention but did not directly affect actual pro-environmental behaviour. These findings support the TPB framework that attitudes, subjective norms and PBC are a key predictor of behavioural intention.

However, the link between attitudes and behavioural intention is not always straightforward. Tikir and Lehmann (2011) found that attitude was the strongest predictor of intention. Tikir and Lehmann (2011) also emphasised the role of values, egalitarianism and individualism, as key factors that shape attitudes and subjective norms, which in turn influence behavioural intentions. Their findings suggest that even when students have pro-environmental attitudes, intention may not follow if these attitudes are not supported by strong social norms or internalised values. This insight is particularly relevant in the university context, where students may be aware of sustainability issues, however they face external challenges. These challenges can be a lack of infrastructure or institutional support, which may hinder the translation of intention into action.

These findings suggest that while awareness is a critical starting point, its influence on behavioural intention often depends on other factors such as attitudes, subjective norms, and internalised values. Awareness may help explain why sustainability matters but changing this understanding into intention often requires addressing personal motivations and external barriers.

Moreover, the way TPB constructs contribute to the behavioural intention can also vary depending on context. Tsai and Tan (2022), in their exploration of environmental protection behaviours among undergraduates, found that PBC was the strongest predictor of intention, followed by attitude and subjective norms. Moreover, moral norms strongly predicted subjective norms and PBC, and moderately predicted attitudes. Their results suggest that when students feel a sense of moral responsibility and confidence in their ability to act, they may form strong intentions regardless of other factors. These findings bring to light the flexibility of the TPB framework across different behavioural contexts.

These insights also underline the role of institutional context. In structured environments, such as universities, clear norms and visible support systems may strengthen pro-environmental intentions, even when individual awareness is limited. Universities can therefore play a central role in shaping students' behavioural intention by providing guidance and access to resources that support sustainable action.

Similarly, Correia et al. (2022) discovered that subjective norms and PBC were the only significant predictors of pro-environmental intention among university students. In contrast, environmental knowledge and attitude did not show a statistically significant effect on intention. Furthermore, intentions and PBC positively predicted actual behaviour. These findings further support the role of social expectation and belief in one's ability to act within the TPB framework. Correia et al. (2022) suggest that even when students are environmentally knowledgeable or hold positive attitudes, these factors alone may not lead to a successful development of pro-environmental intentions. This reinforces the relevance of focusing on subjective and control-related factors when trying to promote sustainable behaviours in university settings.

Furthermore, Macovei (2015) also studied pro-environmental behavioural intention among students using a model that included elements of the TPB. While the study incorporated additional factors, Macovei's (2015) findings align with the idea that awareness of consequences directly and significantly predicts intention, along with subjective norms, attitudes and PBC. Additionally, intention was found to significantly predict pro-environmental behaviour. This also reinforces Wu et al. 's (2022) study that awareness can play a direct role in shaping pro-environmental behavioural intention.

Sociodemographic variables can significantly influence the dynamics between awareness, attitudes and behavioural intentions. Tsai and Tan (2022) discovered that PBC was the strongest predictor of environmental protection intention among first-year students, while attitude and subjective norms played a more important role among higher class standings. This suggests that as students advance through university and gain more education on sustainability, the more they rely on internalised attitudes and social expectations in their decision making. Tsai and Tan (2022) found no clear gender differences in pro-environmental intentions. Similarly, Phang and Ilham (2023) also reported no statistically significant difference in pro-environmental behaviour between male and female students. They attributed these results to evolving gender roles and the broad accessibility of environmental information.

To add on, Tikir and Lehmann (2011) highlighted that cultural backgrounds may influence how behavioural intentions are formed. They proposed that students from regions more affected by environmental degradations might be more accustomed to sustainability concerns, however this was not empirically tested. More notably, Tikir and Lehmann's (2011) findings showed that students from collectivist cultures were more likely to align their intentions with social expectations, whereas students from individualistic cultures were

influenced more by personal beliefs. This distinction suggests that cultural orientation could affect how strongly subjective norms or attitudes predict intention.

The overview of the reviewed empirical studies collectively demonstrates that awareness, attitudes, subjective norms, PBC and behavioural intention are closely linked, but their influence varies depending on context. Wu et al. (2022) and Phang and Ilham (2023) provided insights into the role of awareness in shaping intention. However, Correia et al. (2022) and Tsai and Tan (2022) point towards subjective norms and PBC as stronger predictors of intention. Tikir and Lehmann (2011) and Macovei (2015) further suggest that cultural orientation and background factors may influence how TPB constructs interact.

These patterns underscore that the influence of TPB constructs on behavioural intention is not uniform, but they are shaped by differences in context, culture and student characteristics.

2. Empirical research on awareness and behavioural intention toward sustainable AI use among students

2.1. Methodology of the empirical study

In this subchapter, the author will discuss the methodology used to conduct the empirical part of this thesis. This study aims to quantitatively investigate how university students' awareness of the environmental impact of AI influences their attitudes, subjective norms, PBC and behavioural intentions regarding sustainable AI practices.

The methodology is divided into the following key stages: reviewing relevant literature, compiling the questionnaire, distributing the questionnaire, collecting and cleaning the data, analysis in STATA and interpreting the results. Please see Figure 2, to see the description of the process.

After analysis and overview of empirical literature, the author compiled an online questionnaire using relevant measurement tools. The survey was divided into two main sections: socio-demographic factors and the constructs derived from TPB.

For the first section of the questionnaire, a set of socio-demographic questions were included to conduct comparative analysis across the different student groups. Additionally, they were included to explore whether background variables affect awareness, attitudes or behavioural intentions related to sustainable AI. The questions cover four key categories: age, gender, year of study and educational background related to AI and sustainability.

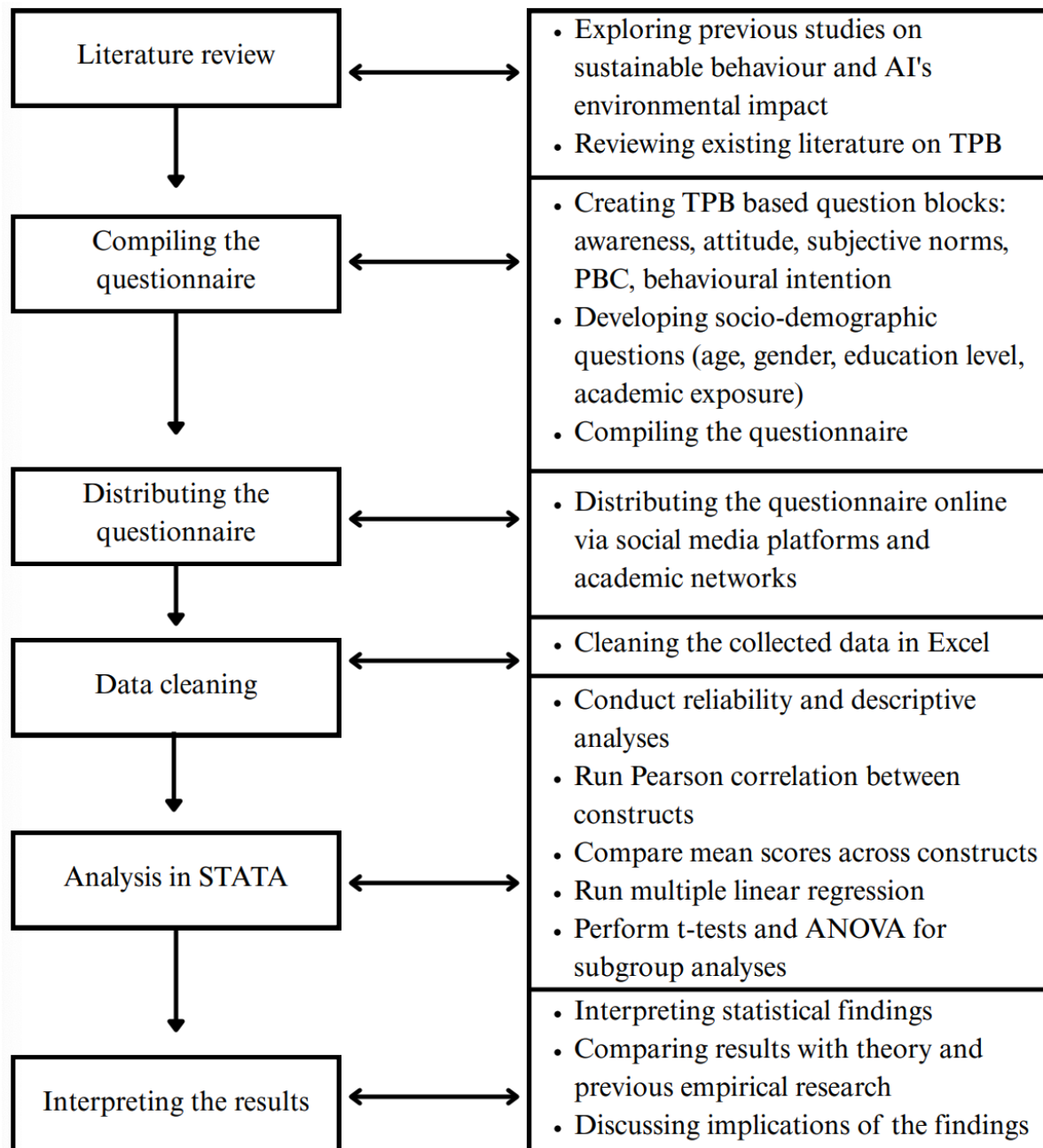


Figure 2: Methodology of the research

Source: Compiled by the author

The decision to include the previously mentioned variables was based on the findings of previous studies. Tsai and Tan's (2022) findings revealed that class standings significantly influenced TPB constructs. PBC was the strongest predictor of intention among first-year students, while attitudes and subjective norms became more important for students in higher years. This pattern suggests that as students gain more exposure to environmental education, they may increasingly rely on internalised values and social expectations, hence the author's decision to include this variable in the questionnaire. Phang and Ilham (2023) also included gender and academic background into their analysis, they noted that although some

demographic effects were not statistically relevant, such variables remain a critical point for understanding variance in environmental behaviours. Drawn from previous insights, the author's decision to include similar demographic questions was to test for comparable patterns in the context of sustainable AI.

Moreover, two questions were designed by the author to determine the participants' academic exposure to appropriate subjects. These questions asked whether students had taken a course introducing the fundamentals of AI and whether they had attended a course where environmental sustainability was a primary focus. They were included based on the author's assumption that prior educational exposure may influence both awareness and PBC. Additionally, they were intended to enable subgroup comparisons later in the analysis. All socio-demographic questions can be found in Appendix A.

As mentioned in the previous chapter, TPB provides the conceptual basis for the second section of the questionnaire. In the following part, the author established five question blocks that correspond to the TPB constructs: awareness, attitudes, subjective norms, PBC and behavioural intentions. The newly adapted structure used in this study positions awareness as a foundational variable that influences all three core TPB predictors and also behavioural intention. Which is consistent with previous empirical applications in the environmental context.

While not an original construct in Ajzen's (1991) TPB, awareness has been adapted into TPB based studies in the environmental field due to its indirect yet vital influence on the original TPB constructs (Wu et al., 2022; Macovei). Existing awareness items typically focus on concepts such as resource scarcity and climate change. To fit to the AI context, these items were adapted to reference issues such as energy consumption of AI and the lack of public discussion around the topic of sustainability of AI. An item about energy conservation was adapted to: "I am aware that the development and training of AI models consumes significant energy."

In the second question block, the author focused on measuring students' attitudes towards sustainable AI practices. In the TPB model, attitudes refer to whether an individual has a favourable or an unfavourable opinion towards the behaviour in question (Ajzen, 1991). Studies such as Tsai and Tan (2022), Correia et al. (2022) and Macovei (2015) included general pro-environmental statements such as "I believe that environmental protection is very important". The author adapted this to the AI context such as "I believe integrating sustainability into AI is valuable". Through this the author ensured that components of attitude were retained, while keeping the focus on AI.

The third block of the questionnaire evaluated subjective norms, which in the TPB framework refer to an individual's perception of social pressure to perform or not perform a given behaviour (Ajzen, 1991). Items were adapted from Wu et al. (2022) and Correia et al. (2022) and they focused on peer influence in the environmental context. As an example, an item focusing on peer behaviour around recycling was adjusted to "My peers think it's important to use AI in a responsible and environmentally conscious way".

The fourth question block assessed PBC, which refers to a person's perception of their ability to carry out a particular behaviour including perceived ease or difficulty and access to opportunities or resources that are necessary (Ajzen, 1991). The author adapted items from Tsai and Tan (2022), Correia et al. (2022) and Macovei (2015) to reflect students' confidence to act sustainably with AI. As an example, a statement regarding self-efficacy was adapted as "I know what steps to take to engage with AI in a more sustainable way".

The final block of the questionnaire examined behavioural intentions, which in the TPB represent the motivational factors that influence a person's readiness to perform a behaviour (Ajzen, 1991). The items originally focused on environmental behaviours; however, they were adapted to reflect students' intentions of engaging in sustainable AI-related practices in the future. Such as adapting "I intend to use natural resources in a responsible manner" to "I plan to choose AI tools that are more environmentally sustainable".

All questionnaire items in the TPB based sections were measured using a 6-point Likert scale to capture the degree of agreement with each statement: 1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree and 6 = Strongly agree. Two additional response options were included: *a = Not applicable and *b = Do not wish to answer. All TPB questions can be found in Appendix B.

After finishing the final version of the questionnaire, the survey was distributed online using a non-probability sampling method. This was done to ensure broad participation across different academic backgrounds and education levels, a combination of convenience sampling and snowball sampling was employed. Initially, the author shared the questionnaire through social media platforms and personal academic networks and participants were encouraged to share the survey with fellow university students. Through this method, the author aimed to maximise the number of respondents and to ensure the inclusion of a diverse student pool across multiple universities.

The survey targeted university students across all levels of study, regardless of their field of study. While the author of this study is affiliated with the University of Tartu, the study did not limit participation to this institution. The decision to also target students outside

the University of Tartu was based on the assumption that awareness and behavioural intention towards sustainable AI is shaped by general educational experiences. At the end of the data collection the total number of responses was 136 and the sample characteristics can be found in Table 3.

Table 3

Sample characteristics

Variable	Category	Frequency	Percentage
Age	18	5	3.68%
	19	13	9.56%
	20	22	16.18%
	21	26	19.12%
	22	30	22.06%
	23	24	17.65%
	24	13	9.56%
	25	1	0.74%
	26	1	0.74%
	28	1	0.74%
Gender	Male	63	46.32%
	Female	67	49.26%
	Other	3	2.21%
	Prefer not to say	3	2.21%
Study level	Bachelor's Degree	126	92.65%
	Master's Degree	10	7.35%
Taken AI-related university course	Yes	58	42.65%
	No	78	57.35%
Taken sustainability-related university course	Yes	69	50.74%
	No	67	49.26%

Note: N =136

Source: Compiled by the author

The final sample primarily consisted of students currently enrolled in bachelor's degree programs (92,65%) across multiple universities. The age of the respondents ranged from 18-28, however the majority concentrated between the ages of 20 and 23. Most participants of the questionnaire identified as either male (46,32%) or female (49,26%), only a small number of participants selected "other" or preferred not to disclose their gender. To account for prior educational exposure, participants were also asked to whether they had attended a course related to AI or sustainability. Slightly more than half (57,35%) of students

had not taken an AI-related course, however 50,74% of the students reported to have attended a sustainability-related course.

Before the final stage, after the responses were collected, the data was cleaned in Excel and then loaded into STATA for analysis. Firstly, the internal consistency of each TPB construct was tested through reliability testing. This was followed by descriptive statistics to summarise central tendencies and variation across the studied variables. Additionally, mean values across the different constructs were compared to identify if there are any systematic differences, which can offer insight into the relative strength of each construct. Next, subgroup analyses were conducted by using independent sample t-tests and one-way ANOVA to compare the TPB constructs across demographic and educational background variables. Furthermore, correlations between the TPB constructs were measured using the Pearson's correlation coefficient to discover potential associations. Finally, a multiple linear regression model was applied to test how awareness, attitudes, subjective norms and PBC predicted behavioural intentions.

The final stage involved presenting and discussing the results, comparing them to the TPB model and previous empirical studies. This approach aimed to offer a comprehensive overview of the factors influencing students' behavioural intentions toward sustainable AI practices.

2.2. Results and interpretation of TPB-based student responses on sustainable AI practices

In the following subchapter, the results of the conducted questionnaire are presented. Reliability analysis was conducted using Cronbach's Alpha to determine the internal consistency of the TPB constructs. As the measurement items were taken from previous studies and adapted to the context of sustainable AI, verifying their reliability was essential. One item from the awareness construct was excluded after the 4 items produced a Cronbach's Alpha value of 0,52. After the adjustment, all constructs met the accepted reliability threshold of 0,70, indicating adequate internal consistency. As seen in Table 4, Cronbach's Alpha values ranged from 0,71 to 0,86, with the highest reliability observed for behavioural intention.

Table 4

Reliability analysis of measurement tools

Factor	Cronbach's Alpha	Number of items
Awareness	0,71	3
Attitudes	0,71	4
Subjective norms	0,80	4
Perceived behavioural control	0,77	4
Behavioural intention	0,86	4

Source: Compiled by the author

After the reliability analysis the author will continue with the descriptive statistics. As mentioned in the previous subchapter, all items were measured on a 6-point Likert scale ranging from 1 (Strongly disagree) to 6 (Strongly agree). From Table 5, it can be seen that students reported the highest levels of agreement for awareness ($M = 5,08$), followed closely by attitudes ($M = 4,74$). Behavioural intention also received relatively high agreement ($M = 4,36$). These high results may indicate strong internal motivation and interest in sustainable AI. In contrast, lower mean values were observed for subjective norms ($M = 3,84$) and PBC, with PBC scoring the lowest ($M=3,20$). This may suggest that students feel less social pressure and have limited confidence in their ability to adopt sustainable AI behaviours.

Table 5

Descriptive statistics of studied variables

Factor	Mean	Median	Std. Deviation	Minimum	Maximum
Awareness	5,08	5,17	0,74	2,00	6,00
Attitudes	4,74	4,75	0,69	3,00	6,00
Subjective norms	3,84	3,88	0,91	1,50	6,00
PBC	3,20	3,25	0,98	1,00	5,25
Behavioural intention	4,36	4,50	0,80	2,75	6,00

Note: $N = 124$

Source: Compiled by the author

To further examine whether these apparent gaps between constructs were statistically meaningful, the author conducted paired sample t-tests between all construct pairs. Table 6 presents the resulting mean differences, all of which were statistically significant at the 0,01 level. The largest gap was measured between awareness and PBC ($M_{diff} = 1,88$), followed by attitudes and PBC ($M_{diff} = 1,54$). This reinforces the notion that while students may feel informed and positive about sustainable AI, they may not feel empowered to act accordingly. Differences between behavioural intention and PBC were also substantial, suggesting that confidence in one's ability to act may not be a more critical barrier than personal motivation.

Table 6

Mean Differences Between TPB Constructs (Paired t-tests)

Factor	1	2	3	4	5
1. Awareness					
2. Attitudes	0,34**				
3. Subjective norms	1,24**	0,90**			
4. PBC	1,88**	1,54**	0,64**		
5. Behavioural intention	0,72**	0,38**	-0,52**	-1,16**	

Note: Values represent mean differences (column - row) from paired sample t-tests;

**Comparison is significant at the 0.01 level (2-tailed); N = 124

Source: Compiled by the author

These findings suggest a meaningful gap between what students know and value, and how capable they feel of turning those intentions into action, a dynamic that becomes relevant in the regression analysis that follows.

Additionally, this pattern suggests a potential hierarchy and clustering among the constructs: awareness, attitudes and intention form a high-scoring group, while subjective norms and PBC cluster at the lower end. This could indicate that students understand and support AI in principle, however external (peer expectations) and internal (self-efficacy) barriers may hinder their behavioural follow-through. These results reflect the findings of Tikir and Lehmann (2011), they noted that even when pro-environmental attitudes are present, behavioural intention may not follow if these attitudes are not supported by strong social norms or PBC.

Moreover, the high awareness score may also reflect a self-enhancing tendency in the questionnaire responses. University students could be overestimating their actual awareness, as self-assessments can be prone to bias, especially in the academic setting where sustainability and AI are becoming a more important topic. Therefore, it is crucial to interpret high awareness with some caution, as it might not translate into behavioural competence.

In order to better understand the potential influence of individual and educational characteristics on responses, several subgroup comparisons were carried out. These included analyses based on gender, AI-related course exposure, sustainability-related course exposure and age group, which allowed the exploration of potential variations across the TPB constructs.

While prior studies have frequently shown that women report to have stronger pro-environmental attitudes and behaviours than men (Milfont & Sibley, 2016), no statistically significant gender differences were observed in the TPB constructs in this study. Please see

Appendix C. Independent samples t-tests revealed similar mean scores across all five variables for male and female students. This suggests that gender did not play a meaningful role in shaping awareness, attitudes, subjective norms, PBC or behavioural intention in this context. These results may reflect a narrowing gender gap in environmental concern among the younger generations, potentially due to the widespread accessibility of sustainability-related education. These findings may also suggest a ceiling effect, as overall levels of awareness and intention were already high across the sample, which leaves limited room for gender-based variation to emerge.

Additionally, to gender, the author also analysed whether prior exposure to relevant university coursework influenced students' responses to the TPB constructs. Two types of courses were examined separately: those related to AI and those related to sustainability. The aim was to analyse whether targeted educational experiences corresponded with differences in awareness, attitude, subjective norms, PBC and behavioural intention regarding sustainable AI practices.

Firstly, the author focused on students who had taken an AI-related course. As seen in Table 7, several statistically significant differences were discovered. Students who had taken an AI-related course reported higher PBC ($M = 3,66$ vs $2,89$), which suggests that they have greater confidence in their ability to act sustainably within the AI context. They also scored higher on subjective norms ($M = 4,09$ vs $3,64$), indicating stronger perceptions of social expectations related to sustainability behaviour. In addition, behavioural intention was significantly higher in this group ($M = 4,51$ vs $4,17$), although no significant differences were observed in awareness or attitudes.

Table 7

Comparison of TPB constructs by university students who have taken an AI-related course

TPB Construct	Yes (Mean)	No (Mean)	N (Yes)	N (No)	Mean difference	t	p
Awareness	5,02	5,06	57	78	-0,04	-0,30	0,76
Attitudes	4,80	4,65	56	76	0,15	1,20	0,23
Subjective norms	4,09	3,64	56	74	0,45	2,93	0,00**
PBC	3,66	2,89	58	77	0,77	5,00	0,00**
Behavioural intention	4,51	4,17	57	76	0,34	2,28	0,02*

Note: p-values based on independent samples t-test; ** Statistically significant at $p < 0.01$; *

Statistically significant at $p < 0.05$.

Source: Compiled by the author

Secondly, the author focused on students who had taken a sustainability-related course. As seen in Table 8, this group also reported significantly higher subjective norms ($M = 4,16$ vs $3,47$), along with a modest but statistically significant increase in PBC ($M = 3,38$ vs $3,05$). While behavioural intention was again higher among sustainability-related course participants ($M = 4,44$ vs $4,18$), the results did not reach statistical significance. Similar to the AI-course group, no meaningful difference was observed in awareness or attitudes between those who had and hadn't taken a sustainability-related course.

Table 8

Comparison of TPB constructs by university students who have taken a sustainability-related course

TPB Construct	Yes (Mean)	No (Mean)	N (Yes)	N (No)	Mean difference	t	P
Awareness	4,98	5,12	69	66	-0,14	-1,09	0,28
Attitudes	4,70	4,73	67	65	-0,03	-0,26	0,80
Subjective norms	4,16	3,47	68	62	0,69	4,74	0,00**
PBC	3,38	3,05	69	66	0,33	2,01	0,05*
Behavioural intention	4,44	4,18	68	65	0,26	1,74	0,08

Note: p-values based on independent samples t-test; ** Statistically significant at $p < 0.01$; * Statistically significant at $p < 0.05$ (PBC p-value = 0.0459).

Source: Compiled by the author

Analysed together, these findings suggest that course exposure, whether AI-related or sustainability-related, is associated with higher perceived social expectations and a greater confidence to act sustainably. These are both key motivational drivers in the TPB however, somewhat surprising is the findings that awareness and attitudes did not differ significantly between the groups. Given that these courses are designed to convey knowledge (awareness) and promote sustainable values (attitudes), the lack of a significant difference in these areas is unexpected. This may suggest that course-based interventions shapes how capable and socially supported students feel, rather than changing what they know or believe.

Lastly, the author analysed the age group differences using one-way ANOVA. Since age was collected as a continuous variable in the questionnaire, respondents were divided into three approximately equal groups for the purpose of this analysis: 18-20, 21-22 and 23 years of age and older. No statistically significant differences were observed across any of the TPB constructs, at a 0,05-significance level. Please see Appendix D. Although students in the 23

and older age group reported slightly higher mean scores on PBC and behavioural intention, these trends were not strong enough to reach statistical significance.

These results contrast with the findings of Wang et al. (2021), they observed that pro-environmental behaviour tends to increase with age, particularly among individuals aged 65 and above. This lack of significant difference in the current thesis may be attributed to the relatively narrow age range of the sample, as all participants were university students in early adulthood. Broader age-based trends in sustainability may emerge when the sample is more diverse and age-groups more spread out.

To explore the relationships between the TPB constructs a Pearson correlation analysis was conducted. Table 9 displays the correlation coefficients between awareness, attitudes, subjective norms, PBC and behavioural intentions. All variables were positively correlated, and most correlations were statistically significant at the 0.01 level with one exception.

Table 9

Correlation between TPB constructs

Factor	1	2	3	4	5
1. Awareness	1,00				
2. Attitudes	0,67**	1,00			
3. Subjective norms	0,22*	0,35**	1,00		
4. PBC	0,23**	0,40**	0,53**	1,00	
5. Behavioural intention	0,57**	0,63**	0,50**	0,33**	1,00
N	135	132	130	135	133

Note: *. Correlation is significant at the 0.05 level (2-tailed); **. Correlation is significant at the 0.01 level (2-tailed)

Source: Compiled by the author

Based on the findings, the strongest correlations with behavioural intention were found for attitudes ($r = 0,63$), followed by awareness ($r = 0,57$) and subjective norms ($r = 0,50$). These results indicate that students who hold more favourable attitudes, feel more informed and perceive social expectations are also more likely to express an intention to act sustainably with regard to AI. On the other hand, however, while PBC was positively correlated with intention ($r = 0,33$), it showed a weaker association compared to the other predictors.

Awareness was most strongly associated with attitudes ($r = 0,67$), suggesting that students who are more aware also tend to hold more favourable views toward sustainable AI. However, its correlation with subjective norms was relatively weak ($r = 0,22$). This suggests that greater awareness does not necessarily coincide with stronger perceived social

expectations, reinforcing earlier observations that awareness and subjective norms may operate somewhat independently.

To determine which of the TPB constructs significantly predict behavioural intention, a multiple linear regression analysis was conducted. Prior to this, standard assumptions were tested and met, there was no multicollinearity, visual inspection of the residual plots confirmed approximate normality and homoscedasticity. The regression model itself was statistically significant, $F(4,119) = 27,73$, $p < 0,001$, with an R squared of 0,483 (adjusted R squared = 0,465), which indicates that nearly half of the variance in behavioural intention could be explained by the TPB constructs. The regression analysis results can be seen in Table 10.

Table 10

Multiple linear regression predicting behavioural intention

Predictor	β	SE	t	p
Awareness	0,25	0,09	2,61	0,01*
Attitudes	0,37	0,11	3,37	0,00**
Subjective norms	0,29	0,07	4,19	0,00**
PBC	0,01	0,07	0,19	0,85
Constant	0,21	0,41	0,51	0,61

Note: *. Significant at the 0.05 level; **. Significant at the 0.01 level; β = unstandardized regression coefficient; SE = standard error; CI = confidence interval; N = 124.

Source: Compiled by the author

Attitudes emerged as the strongest predictor ($\beta = 0.37$), followed by subjective norms ($\beta = 0.29$) and awareness ($\beta = 0.25$). These results suggest that intention to engage in sustainable AI behaviour is shaped more by evaluative beliefs, perceived expectations and awareness, than by PBC, as PBC was not a significant predictor in this model.

The results of this study offer both supportive and contradictory evidence to earlier empirical findings on pro-environmental behaviour within the TPB framework. In line with Tikir and Lehmann (2011), attitudes emerged as the strongest predictor of behavioural intention in this thesis, followed by subjective norms. This confirms the key role of evaluative beliefs in shaping intention. Additionally, Macovei (2015) found that attitudes, subjective norms and awareness significantly predicted intention, which supports the view that pro-environmental motivation is shaped by a combination of personal values and social influence. Moreover, the strong correlation between attitudes and intention ($r = 0,63$), alongside its dominant role in the regression model ($\beta = 0,37$), reinforces the importance of personal evaluation in motivating students to engage in sustainable AI practices.

To add on, subjective norms also played a statistically significant role in both correlation and regression analysis, suggesting that perceived social expectations from peers, educators or institutions are important influences on behavioural intention. These findings align with both Phang & Ilham (2023) and Correia et al. (2022), who found that subjective norms were strong predictors of intention. Interestingly, even though subjective norms showed a weaker correlation with intention ($r = 0,50$) than attitudes and awareness, they kept a significant contribution in the regression model ($\beta = 0,29$). This supports the idea that, even after accounting for other motivational drivers, social expectation can still have an impact.

One of the more unique findings of this thesis is the statistically significant role of awareness in predicting behavioural intention ($\beta = 0,25$). This supports extensions of the TPB that include awareness as a relevant precursor. This complements the findings of Macovei (2015), who found that awareness significantly and directly predicted behavioural intention, and Wu et al. (2022), who showed that environmental knowledge can also have an indirect role through other constructs such as personal norms and PBC. While awareness had the second highest correlation with intention ($r = 0,57$), its lower beta coefficient in regression suggests that part of its effect may be shared with other constructs. Nonetheless, its independent predictive value underscores the importance of informational interventions as a basis for forming behavioural intention.

In contrast, PBC was not a significant predictor in the regression analysis ($\beta = 0,01$, $p = 0,85$), despite showing a weak positive correlation with intention ($r = 0,33$). This stands in contrast to the findings of Tsai and Tan (2022) and Correia et al. (2022), where PBC was among the strongest predictors of intention and actual behaviour. A possible explanation is that students in this sample may feel informed and motivated; however, they lack a clear sense of agency in acting sustainably within the context of AI.

While this thesis focuses on analysing direct relationships between the TPB constructs by using multiple linear regression, it is also important to acknowledge the potential value of Structural Equation Modelling (SEM) for future research. SEM would allow for the analysis of both direct and indirect effects of the TPB constructs, and could reveal how certain constructs, such as awareness, engage through other variables like attitudes or subjective norms. Awareness may not only shape behavioural intention directly, but also indirectly by strengthening favourable attitudes or reinforcing perceived social expectation. This perspective is also supported by Wu et al. (2022), as they found that environmental awareness influenced behaviour both directly and indirectly through constructs such as personal norms and PBC. These indirect pathways were not analysed in the current thesis but could offer a

more nuanced understanding of how awareness, attitudes and subjective norms shape intention. Incorporating SEM into further studies would therefore enable a more comprehensive test of the extended TPB model.

To conclude, in this subchapter, the author presented the results of the questionnaire analysis using a structured quantitative approach. The data were examined through descriptive statistics, comparison of mean scores across the TPB constructs, subgroup comparisons and correlation and regression analyses. These results were then interpreted in comparison to previous findings.

This research has a few implications. Firstly, the results confirmed some well-established patterns observed in previous studies. Attitudes consistently emerged as the strongest predictor of behavioural intention, aligning with the findings of Tikir and Lehmann (2011). Similarly subjective norms also played a vital role, reinforcing the importance of perceived social expectations in sustainability-related behaviour. These results support the strength of the TPB framework when applied to the topic of sustainable AI.

On the other hand, this thesis also uncovered several findings that diverge from earlier research. Most notably, PBC did not significantly predict intention, despite being a key construct in the TPB and a significant factor in studies by Tsai and Tan (2022) and Correia et al. (2022). This raised a new question regarding students' perceived agency in the context of AI, and whether institutional barriers are limiting their sense of control. In addition, awareness, although not originally part of the TPB framework, was found to be a significant predictor of intention.

Furthermore, mean comparison revealed a clear divide between the TPB constructs. Awareness, attitudes and intention showed relatively high agreement among students, whereas subjective norms and PBC scored noticeably lower. This suggests that while students may be internally motivated and well-informed, they might not feel socially encouraged or practically equipped to act. These findings open up a new area for research into how universities or policymakers can support not only student motivation but also the social and structural conditions needed to encourage sustainable AI behaviours.

Lastly, while this study focused on testing direct relationships between variables, future research could benefit from employing SEM to examine indirect effects. A more comprehensive modelling approach would allow for a deeper understanding of how these behavioural processes interact, such as how awareness might influence intention through its impact on attitudes or subjective norms.

Conclusion

AI has embedded itself into the daily lives of university students, especially through tools that support academic work. While these advancements in technology offer efficiency and learning benefits, they also come with increasing environmental costs due to high energy consumption and a reliance on fossil fuel-based infrastructure. As AI becomes a more integrated part of education, understanding how students perceive its sustainability implications becomes more important, given their potential role as both users and future developers of these technologies. Moreover, the discussion of AI's dual role, as both a solution and a sustainability challenge, underscores the relevance of exploring how awareness might shape more responsible behaviours.

Previous empirical studies have shown that attitudes, subjective norms, PBC and awareness are all relevant in explaining environmentally responsible behaviour among students. While attitudes, subjective norms and PBC predict intention, awareness can also play a central or supporting role depending on the context. The previous empirical studies revealed that TPB can be adapted to include awareness as a key construct, and that cultural, institutional and personal influences affect how students form behavioural intentions. These findings provided a foundation for discovering how students engage with sustainable AI and how personal motivation interacts with perceived external constraints.

This thesis adopted a quantitative approach to explore university students' awareness, and behavioural intention regarding sustainable AI practices. Using an extended TPB model that included awareness, the data was collected from students using a questionnaire that measured key TPB constructs along with demographic and educational background variables. The data collection process was designed to explore both the students' individual attitudes and broader social influences. Additionally, whether education in AI or sustainability had any impact on how the students responded.

Descriptive statistics results revealed that students rated their awareness and attitudes highly, along with strong behavioural intentions. However, their subjective norm and PBC levels were notably lower. This gap suggests that while students may value sustainability, they may not feel supported or capable of acting in ways that align with those values. Further analysis confirmed a significant difference between these constructs, noticeably between intention and PBC. These differences suggest an imbalance between internal motivation and practical ability to act.

Moreover, additional comparisons across gender, age and course participation revealed that students who had taken AI or sustainability-related courses reported higher PBC

and subjective norms. This suggests that targeted education can strengthen a student's confidence and perceived social support for sustainable AI behaviour. However, these courses did not significantly raise awareness or change attitudes, which may indicate that students already hold strong views on sustainability and that the role of education is more about enabling action than shaping these initial beliefs.

The correlation analysis confirmed that attitudes, awareness and subjective norms were positively related to behavioural intention, with attitudes showing the strongest association. Furthermore, in the regression model, attitudes, subjective norms and awareness all significantly predicted intention, while PBC did not. This suggests that students feel informed and motivated, they may not feel fully able to act due to external or internal barriers. This also reinforces the importance of internal and social motivations, while drawing attention to gaps in confidence or practical ability.

Beyond confirming the findings with earlier empirical studies, this research offers new insights into how students engage with AI. The inclusion of awareness as a predictor supports calls to expand behavioural model in emerging contexts. The low levels of PBC and subjective norms highlight a gap that educational institutions may need to address if they wish to promote more sustainable engagement with AI. Moreover, the gap between high motivations and low perceived control raises questions about how institutional or contextual barriers are influencing students' ability to act on their intentions.

Finally, while the current thesis focused on direct relationships between the TPB constructs, future research could explore the indirect pathways, such as whether awareness strengthens attitudes or subjective norms, which in turn influences intention. SEM could help to uncover these deeper dynamics and further refine how behavioural models are applied to complex issues such as sustainable AI.

This research also has some limitations. One of them is the relatively small sample size ($N = 136$), which limits how broadly the results can be generalised. In addition, in this thesis, the sample was heavily skewed towards bachelor's students (92,65%), making it less representative of the broader university population. The students may have also overestimated their levels of awareness or behavioural intention, especially in a context where sustainability is viewed as a socially desirable trait. Lastly, while awareness was included as an extension to the TPB model, more advanced methods, such as SEM, would be needed to test how awareness may influence intention indirectly through other constructs.

This thesis contributed to the limited research on sustainable AI behaviour among university students by applying and extending the TPB. Overall, it highlighted key

motivational and contextual factors, including the role of awareness. While this thesis identified important patterns, further research is needed to explore how these factors interact over time and across different student populations.

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APPENDIX A

Socio-demographic measurement tools used in the distributed survey

Category	Question	Answers
Age	What is your age? (Please use only numeric values, e.g., 18, 20, 22)	Answers were provided in numeric values
Gender	What is your gender?	• Male • Female • Other • Prefer not to say
Year of study	What is your year of study?	• Bachelor's Degree • Master's Degree • PhD Degree
Educational Background	Have you taken a university course that introduced the fundamentals of AI (e.g., machine learning or large language models)?	• Yes • No
	Have you taken a university course where environmental sustainability was a key focus (e.g., climate change or resource management)?	• Yes • No

Source: Compiled by author

APPENDIX B

Measurement tools for awareness, attitudes, subjective norms, PBC and behavioural intentions regarding sustainable AI used in the distributed survey

Construct	Item	Source
Awareness of the environmental impact of AI	I am aware that the development and training of AI models consumes significant energy.	Macovei (2015)
	I understand that AI can have both positive and negative environmental impacts.	Wu et al. (2022)
	I have encountered the term "sustainable AI" before.	Wu et al. (2022)
	I believe the environmental impact of AI should be a topic of public discussion.	Macovei (2015)
Attitudes toward sustainable AI	Using AI responsibly is beneficial for the environment.	Correia et al. (2022)
	I believe integrating sustainability into AI is valuable.	Tsai & Tan (2022)
	I feel good about supporting sustainable AI development.	Tsai & Tan (2022)
	Reducing the environmental impact of AI is important to me.	Macovei (2015)
Subjective norms	My peers think it's important to use AI in a responsible and environmentally conscious way.	Wu et al. (2022)
	In my academic environment, it's becoming more common to talk about the environmental impact of AI.	Wu et al. (2022)
	I would feel supported by others if I made an effort to learn about sustainable AI.	Correia et al. (2022)
	People I interact with value being informed about how AI affects the environment.	Correia et al. (2022)
	I feel confident that I can choose environmentally responsible AI	Tsai & Tan (2022)

	tools.	
Perceived behavioural control	• I have access to information on the environmental impact of AI systems.	Tsai & Tan (2022)
	• I know what steps to take to engage with AI in a more sustainable way.	Correia et al. (2022)
	• I believe my actions can make a difference in promoting sustainable AI.	Macovei (2015)
Behavioural intentions	• I intend to support sustainable AI initiatives in my future career.	Correia et al. (2022)
	• I plan to choose AI tools that are more environmentally sustainable.	Macovei (2015)
	• I will stay informed about the environmental impact of AI.	Tsai & Tan (2022)
	• I am likely to advocate for sustainable AI in professional settings.	Correia et al. (2022)

Note: All items were measured on a 6-point Likert scale: 1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree and 6 = Strongly agree. Additional options included: *a = Not applicable and *b = Do not wish to answer.

Source: Compiled by author

APPENDIX C

Comparison of TPB constructs by gender

TPB Construct	Male (Mean)	Female (Mean)	N (Male)	N (Female)	Mean difference	t	p
Awareness	5,14	4,96	62	67	0,18	1,31	0,19
Attitudes	4,73	4,71	59	67	0,02	0,18	0,85
Subjective norms	3,83	3,83	59	66	-0,00	-0,01	0,99
PBC	3,31	3,13	62	67	0,18	1,05	0,30
Behavioural intention	4,30	4,33	61	66	-0,03	-0,15	0,88

Note: p-values based on independent samples t-test. No statistically significant difference observed (all $p > 0.05$).

Source: Compiled by the author

APPENDIX D

ANOVA of age groups

TPB Construct	18-20 Mean (N)	Std. dev.	21-22 Mean (N)	Std. dev.	23+ Mean (N)	Std. dev.	F	p
Awareness	5,08 (40)	0,70	4,97 (55)	0,81	5,13 (40)	0,80	0,50	0,61
Attitudes	4,65 (39)	0,78	4,66 (53)	0,68	4,85 (40)	0,76	0,98	0,38
Subjective norms	3,57 (38)	0,96	3,92 (53)	0,77	3,97 (39)	0,97	2,42	0,09
PBC	3,01 (40)	0,97	3,17 (56)	0,93	3,49 (39)	0,96	2,61	0,08
Behavioural intention	4,26 (40)	0,86	4,25 (54)	0,91	4,47 (39)	0,82	0,82	0,45

Note: p-values based on independent samples t-test; one-way ANOVA used to test group differences; no statistically significant differences observed (all $p > 0.05$).

Source: Compiled by the author

Resümee

ÜLIÕPILASTE TEADLIKKUS JA KÄITUMUSLIKUD KAVATSUSED JÄTKUSUUTLIKU TEHISINTELLEKTI KASUTAMISEL

Oscar Sõber

Bakalaureusetöö eesmärk on uurida kuidas üliõpilaste teadlikkus tehisintellekti keskkonnamõjust mõjutab nende kavatsust kasutada tehisintellekti jätkusuutlikult. Tehisintellekti tehnoloogiate lahenduste, näiteks ChatGPT, üha laialdasem kasutamine ülikoolides tõstab esile vajaduse teadvustada nende tehnoloogiate keskkonnamõjusid ja toetada vastutustundlikku kasutust. Üliõpilased on lisaks aktiivsetele kasutajatele ka tulevased arendajad ja valdkonnakujundajad.

Töö teoreetiliseks aluseks on planeeritud käitumise teooria (*Theory of Planned Behaviour*), mille raames uuritakse mudeli põhikonstruktsioone: hoiakuid, subjektiivseid norme, tajutavat käitumiskontrolli ning käitumuslikku kavatsust. Täiendavalt käsitletakse ka teadlikkust, arvestades sellel olulisust keskkonna- ja jätkusuutlikkuse kontekstis. Varasemad empiirilised uuringud on näidanud, et planeeritud käitumise teooria põhikonstruktsioonid ennustavad käitumuslikku kavatsust, kuid teadlikkus võib samuti mängida kas kesket või toetavat rolli.

Bakalaureusetöö koosneb kahest peamisest peatükist. Esimeses peatükis käsitletakse teoreetilist raamistikku, määratledes ja kontekstualiseerides tehisintellekti keskkonnamõju jätkusuutlikkuse vaatenurgast ning tutvustatakse kontseptuaalset lähenemist, milles teadlikkust käsitletakse kui võimalikku eeltingimust jätkusuutlikku käitumise kujunemisel. Samuti antakse ülevaade varasematest uuringutest, mis käsitlevad üliõpilaste jätkusuutlikku käitumist ning planeeritud käitumise teooria põhikonstruktsioone.

Teine peatükk keskendub metodoloogiale ja empiirilisele analüüsile, kirjeldades küsimustiku koostamist, valimi kujundamist ning kasutatud statistilisi meetodeid, sealhulgas kirjeldavat statistikat, keskmiste erinevuste analüüsi, alamrühmade võrdlusi, korrelatsioonianalüüsi ja regressioonianalüüsi. Küsimustikule vastas kokku 136 üliõpilast, kelle vastuseid kasutati tehisintellekti jätkusuutliku kasutamise kavatsuste ja nendega seotud tegurite analüüsimiseks. Peatükk lõppeb tulemuste võrdlusega varasemate empiiriliste uuringutega ning tuuakse esile järeldused, mis toetavad jätkusuutliku tehisintellekti kasutamise edendamist üliõpilaste seas.

Tulemused näitavad, et üliõpilased hindasid oma teadlikkust ja hoiakuid jätkusuutlikku tehisintellekti suhtes kõrgeks ning väljendasid suhteliselt tugevaid käitumuslikke kavatsusi. Siiski olid subjektiivsete normide ja tajutava käitumiskontrolli

hinnangud märgatavalt madalamad, mis viitab sellele, et kuigi üliõpilased tunnevad end motiveerituna ja informeerituna, võib neil puududa võimalik sotsiaalne tugi või enesekindlus jätkusuutlike tegevuste rakendamisel. Alamrühmade võrdlused näitasid, et üliõpilased, kes olid läbinud tehisintellekti või jätkusuutlikkuse teemalisi kursusi, teatasid oluliselt kõrgemast tajutavast käitumiskontrollist ja subjektiivsetest normidest, kuid teadlikkuses või hoiakutes erinevusi ei täheldatud. Korrelatsioonanalüüs näitas, et hoiakud, teadlikkus ja subjektiivsed normid olid positiivselt seotud käitumusliku kavatsusega, aga tajutaval käitumiskontrollil oli kõige nõrgem korrelatsioon.

Regressioonimodelis osutusid tugevaimateks mõjuteguriks hoiakud, millele järgnesid subjektiivsed normid ja teadlikkus, kusjuures tajutav käitumiskontroll ei avaldanud olulist mõju. Need tulemused rõhutavad kognitiivsete ja normatiivsete tegurite olulisust jätkusuutlike tehisintellekti kavatsuste kujundamisel ning osutavad lõhele motivatsiooni ja tajutava tegutsemisvõime vahel. Teadlikkuse roll antud uuringus näitab, et planeeritud käitumise teooria mudelit on võimalik laiendada ja rakendada ka uutes ning arenevates käitumuslikes kontekstides.

Käesolev bakalaureusetöö panustab kasvavasse teaduskirjandusse jätkusuutliku tehnoloogia kasutamise teemal, rakendades käitumisteooriat tehisintellekti kontekstis. Uuring pakub ka praktilisi teadmisi ülikoolidele ja poliitikakujundajatele, kes soovivad edendada vastutustundlikku ja keskkonnateadlikku tehisintellekti kasutamist. Bakalaureusetöö piirangutena tuleb arvestada valimi piiratud suuruse ja demograafilise ühtlusega, samuti võimalikku vastuste ülehindamine kontekstis, kus jätkusuutlikkust on sotsiaalselt kõrgelt väärtustatud. Edasised uuringud võiksid hõlmata suuremaid ja mitmekesisemaid valimeid, pikisuunalist lähenemist ning struktuurivõrrandite modelleerimist, et analüüsida kaudseid seoseid ja pikaajalisi käitumismustreid.

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UNIVERSITY STUDENTS' AWARENESS AND BEHAVIOURAL INTENTIONS
TOWARDS SUSTAINABLE AI ENGAGEMENT

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