RESPONSIBLE IMPLEMENTATION OF AI IN HIGHER EDUCATION: ETHICAL FACTORS GUIDING DUTCH IT TEACHERS

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This study explores the ethical factors that influence teachers in the use of artificial intelligence (AI) in higher education. Employing a mixed methods approach, which includes a Systematic Literature Review (SLR), two focus groups involving IT teachers, a survey, and four interviews, a total of 37 ethical factors were identified through the SLR & focus groups. The ethical factors identified from the literature review and focus groups highlight the nuanced perspectives surrounding the use of AI implementation. The results from the survey and interviews provide an initial step toward further exploration and generalization of the research findings. The findings contribute to a refined understanding of ethical considerations in AI use for teachers, offering valuable insights for higher education stakeholders. The study not only enhances ethical knowledge in AI implementation but also underscores the importance of diverse perspectives in shaping ethical decision-making within the higher education landscape.

Keywords:
artificial intelligence,
AI,
higher education,
teachers,
bachelor IT

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1 Introduction

The rapid growth of artificial intelligence (AI) technology has led to new possibilities and challenges in various domains, including higher education (Raman & Rathakrishnan, 2019). AI's evolving impact on society, particularly in higher education, shows potential e.g. improving learning experiences, administrative efficiency, and educational outcomes (Adiguzel et al., 2023; Chen et al., 2020). However, ethical considerations in AI integration require careful examination to ensure meaningful use (Bonini, 2020). AI is widely used in education for applications like automated essay scoring, dropout prediction, graduate admissions, and knowledge inference (Baker & Hawn, 2022; Ramineni & Williamson, 2013; San Pedro & Baker, 2021; Waters & Miikkulainen, 2014). An example is Jill Watson, an AI bot aiding students as a teaching assistant (McFarland, 2016). However, AI, including machine learning models, may exhibit biases and unfairness (Binns, 2018; Warner & Sloan, 2023). Instances of unfavorable outcomes in education include the University of Texas at Austin discontinuing a biased machine learning system in 2020 (Burke, 2020). Some argue that AI's impact on education quality can negatively affect learning outcomes (Horton, 2023; Ka et al., 2023; Korn & Kelly, 2023; Zhai, 2022). Artificial Intelligence in Education (AIED) technologies aim to enhance education, emphasizing the importance of ethical actions and processes (Hwang et al., 2020; Roll & Wylie, 2016). Teachers must make pedagogical choices mindful of ethics, considering potential (unintended) consequences. Ethical considerations in AI extend beyond technical capabilities to encompass fundamental values and principles in education. Understanding teachers' perceptions of ethical factors in AI adoption in higher education is crucial. AI holds promise in higher education but has diverse ethical implications (Brendel et al., 2021; Pavaloiu & Kose, 2017). AIED may worsen student inequality or commercialize education (Reiss, 2021). Ethical concerns include teachers fearing job loss due to AI automation (Shonubi, 2023). Globally, UNESCO outlines challenges in AI education (Pedro et al., 2019). Even though ethical concerns regarding the use of AI in education are becoming more widespread, research specifically dedicated to higher education is still ongoing. Numerous studies have been conducted to investigate ethical issues associated with the use of AI in higher education (Alexander et al., 2019; Bates et al., 2020; Köbis & Mehner, 2021; Ma & Siau, 2018).

Only a few studies are looking at what teachers think about the meaningful use of AI in education (Amhag et al., 2019; Celik, 2023; Chounta et al., 2022; Lindner & Romeike, 2019; Popenici & Kerr, 2017). There is a lack of research that specifically addresses the ethical concerns related with the use of AI in higher education by Bachelor IT teachers, even though the ethical implications of AI have been extensively studied in a variety of industries (Aoun, 2018; Cox et al., 2019; Holzinger et al., 2019; Loureiro et al., 2021; Verma et al., 2021; Yu et al., 2018). Understanding the attitudes and concerns of teachers towards the use of AI in education is crucial since, for example, they significantly impact how students learn (Lindner & Romeike, 2019). Additionally, these teachers are teaching future IT professionals who will engage with (future) AI technology. Based on the knowledge gap discussed, the following research question is addressed in this paper: *What ethical factors impact the meaningful utilization of (future) AI technology in higher education, as perceived by teachers within the Bachelor IT program?* In this study, "meaningful" refers to the value it adds to education. "Future" encompasses potential applications that are currently unknown.

2 Methodology

To address the research question on ethical factors impacting the use of (future) AI technology in higher education among bachelor IT program teachers, a mixed-methods research design was chosen. This approach, combining qualitative and quantitative methods, provides a comprehensive understanding and validation of results (Brannen, 2017; Leech et al., 2009; Tashakkori & Creswell, 2007). The research commences with a systematic literature review to establish a knowledge base and identify gaps. These gaps are then explored through focus groups and surveys, offering both qualitative and quantitative insights, as well as understanding teacher dynamics. After the focus group sessions, surveys were administered directly after to validate empirical evidence from the literature review. Subsequently, interviews are conducted to delve deeper into teachers' opinions on identified factors discussed in focus groups. Moreover, participants prioritize these factors using q-methodology. Figure 1 provides an overview of the research steps and methods employed.

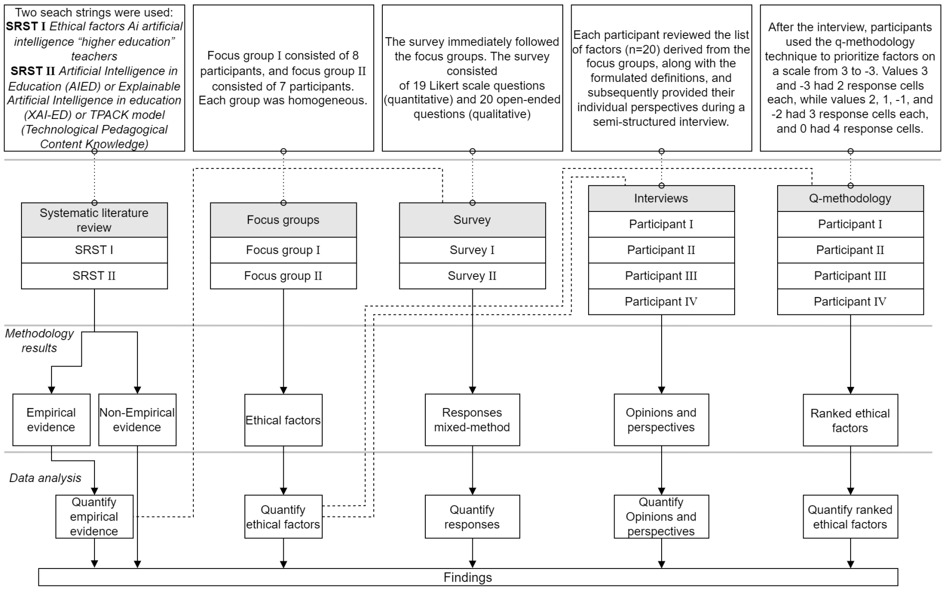

Figure 1: Research process overview
Source: Own

2.1 Systematic literature review

To gain a comprehensive understanding of the existing literature on the research question, a systematic literature review (SLR) was conducted (Nightingale, 2009; Xiao & Watson, 2019). Due to the large amount of available literature, the choice was made to use two search strings (Hao, 2019; Smit et al., 2020; Smit & Van Meerten, 2021). **SRST I:** *ethical factors Ai artificial intelligence "higher education" teachers* and **SRSTII**: *Artificial Intelligence in Education AIED OR Explainable Artificial Intelligence in education XAI-ED OR TPACK model Technological Pedagogical Content Knowledge*. The search period was set between January 2018 and April 2023.

The SLR process was facilitated using the application Publish or Perish and Google Scholar was chosen as the search engine for its broader coverage compared to other search engines (Franceschet, 2010; Harzing & Alakangas, 2016; Jean-François et al., 2013; Wildgaard, 2015). Figure 2 shows the PRISMA flow diagram of both search strings.

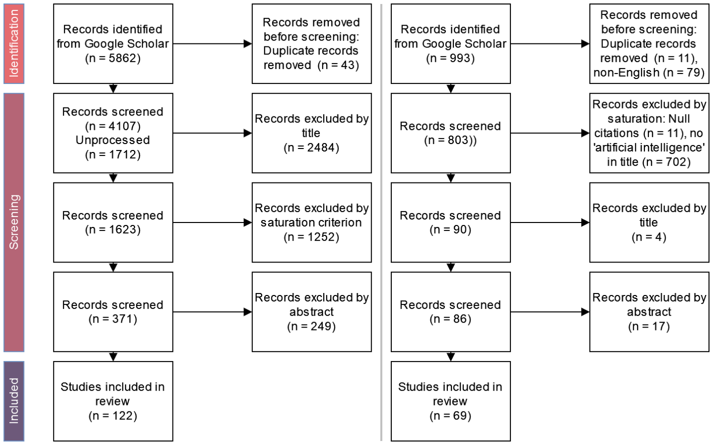

Figure 2: PRISMA flow diagram
Source: Own

With a total of 5819 papers to be screened from SRSTI, ASReview was used for automated screening and selection in the systematic review (ASReview, 2023). To manage the large dataset, two stop criteria were adopted (Callaghan & Müller-Hansen, 2020), meeting either of which would halt the process: (1) surpassing 16 hours analyzing titles or (2) marking more than 50 consecutive titles as irrelevant. A total of 1712 papers were not screened because the time-based stopping criteria (16 hours) was met (Callaghan & Müller-Hansen, 2020). SRSTII didn't require ASReview as the total number of papers to be screened was 803; instead, findings were manually analyzed. Results are categorized into empirical and non-empirical findings. As the study focuses on teachers' opinions, only empirical results, derived from experiments or studies, are considered. This led to a remaining total of 12 papers. Of the 12 papers, eight originated from SRST 1 and four from SRST 2.

2.2 Focus groups & survey

After conducting systematic literature reviews, focus group discussions were held. Two focus group sessions were conducted in June 2023, with 7 and 8 participants each, from a Dutch University of Applied Sciences. The sample included 5 females and 10 males, aged 25 to 66, with work experience of 1 to over 21 years. Moreover, 5 participants had prior AI research experience. At the beginning of each focus group, participants were provided with a brief case study to facilitate the start of the discussions. To gather quantitative data for statistical analysis, a survey was administered immediately after the focus group session, ensuring survey reliability. The survey consisted of 20 sections. The first 19 sections (ethical factors from the SLR) each contained two questions: the first question assessed participants' views on the importance of ethical considerations in AI use in higher education. The second question measured their agreement with the provided explanation) related to ethical factors in AI use in higher education, using a 5-point Likert scale. The last section included an open-ended question for written comments.

2.3 Interviews & Q-Methodology

To generalize data from focus groups, semi-structured interviews were conducted with four IT lecturers from other higher education institutions, three from a University of Applied Sciences, and one from a university. This method allows for a more thorough exploration of topics and enables in-depth probing, providing interviewees the freedom to express opinions without constraints (DiCicco-Bloom & Crabtree, 2006; Fontana, A. & Frey, 2000). Participants were selected based on a comprehensive perspective on education and a strong technical background. Interviews were conducted in June 2023. An interview protocol was developed by one author and validated by a second author. The interviews consisted of two parts: examining and analyzing ethical factors derived from focus groups and prioritizing these factors. 20 ethical factors were presented to interviewees, who were asked if they considered each a relevant ethical factor and to assess the provided explanation/definition. Participants could also share comments and reflections.

In the second part of the interviews, ethical factors were prioritized using the Q-methodology (Brown, 1996), which combines qualitative and quantitative data for a deeper understanding of participants' perspectives. Participants were asked to place the 20 ethical factors from focus groups into specific positions within the pyramid, creating a hierarchy. The comments made by participants during this process were recorded by the interviewer and incorporated into the research analysis.

2.4 Data Analysis

Each paper from the SLR underwent an analysis to identify and document the presence of ethical factors. Papers lacking these factors were still analyzed for other pertinent information. Ethical factors identified in the literature review were categorized based on whether they originated from empirical research. This classification determined inclusion in either the empirical evidence or non-empirical evidence list. A final consolidated list of ethical factors from empirical research was created, combining similar factors and refining descriptions through a validation process with one of the other authors. The developed descriptions were translated into Dutch and reviewed by another author, considering the Dutch-speaking participants. The results from both focus groups, documented on the whiteboard by the participants during the sessions, were transcribed, and combined. The researcher's annotations and audio/video data were integrated for enrichment. Identical ethical factors from both groups underwent consolidation, including synthesized explanations. A secondary review with another author refined the ethical factors further. In the interviews, the interviewer transcribed participant comments for each ethical factor. These transcriptions were then adjacent for each factor, enabling a comparative analysis of participant comments. The data from Q-methodology underwent various analyses. Initially, an overview of all four pyramids was generated for a comprehensive view, aiding in pattern identification. Following this, a table detailing the frequency of ethical factors based on associated scores was created, highlighting frequently encountered factors within each score category. Lastly, a separate table with individual participant scores per ethical factor, including descriptive statistics, was developed.

3 Results

The ethical factors found from both the SLR as well as the focus groups can be found in Table 1.

Table 1: Ethical factors derived from SLR & Focus Group sessions

Ethical factors (SLR or FG)	Description
Accuracy (FG)	It is possible that a student who relies solely on the results of an AI model may be led astray, as there are enough factors within the university that play a role in providing study advice. The accuracy of this advice depends on various aspects. However, how can we determine if the advice is reliable?
Adoption (SLR)	In the context of AI in education, adoption refers to the active integration and approval of AI applications within the university environment, encompassing automation, process acceleration, teaching enhancement, and the establishment of trust through reliability, transparency, and explanatory capabilities. (Bucea-Manea-Țoniş et al., 2022; Chatterjee & Bhattacharjee, 2020; Guàrdia et al., 2021; Keller et al., 2019)
Auditability (FG)	The properties of the AI system must be controllable.
Authorization (FG)	Each role must have the appropriate authorization linked to specific tasks and responsibilities.
Availability (SLR)	In the context of AI in education, available refers to the accessibility and usability of AI systems in universities. These systems encompass chatbots and learning analytics, serving various domains like teaching, administration, and research, with future plans for expansion and the inclusion of multi-language support (Keller et al., 2019).
Bias (FG)	It is essential that the AI application is free from bias. While the model can be trained based on teacher feedback, this must be done carefully. Furthermore, management can use the model to assess the performance of teachers.
Communication of Outcomes (FG)	The communication of an AI model should be objective and sensitive.
Cost (SLR)	In the context of AI in education, cost refers to the financial considerations, evaluation of benefits and risks, and the overall investment required for implementing AI. This also includes the lengthy funding process and the limited availability of funds, both of which can influence the cost of AI implementation (Keller et al., 2019).
Data (SLR)	In the context of AI in education, data refers to responsible data management and ethical handling in AI systems, encompassing risks, ethical implications, discriminatory data, and unfair predictions, with the involvement of data protection officers to ensure proper usage and transparency (Keller et al., 2019; Mâtâ & Boghian, 2019).
Data origin (FG)	Information sources for students can also come from platforms such as Steam or the UWV.

Ethical factors (SLR or FG)	Description
Decision-making (SLR)	In the context of AI in education, decision-making refers to the act of assessing, analyzing, and considering various factors, such as risks, impacts, and performance, in order to make an informed judgment or decision. It encompasses the process of critically examining the different aspects related to the use of AI and determining its potential effects and consequences (Bucea-Manea-Țoniș et al., 2022; Keller et al., 2019; Sangapu, 2018).
Discretionary Authority (FG)	When the outcome of an AI model conflicts with professional judgment, it is important to consider how to handle it.
Education (SLR)	In the context of AI in education, education refers to the importance of introducing courses or topics on the ethical use of AI in the academic environment (Mâtâ & Boghian, 2019).
Explainability (SLR)	In the context of AI in education, explainability refers to the quality exhibited by automated prediction systems in offering dependable explanations for their decisions. This quality ensures a lucid communication and comprehension of the decision-making processes. Explainability directly tackles apprehensions about potential adverse effects, user acceptance, and the mitigation of incomprehensible "black box" systems (Keller et al., 2019).
Feedback (SLR)	In the context of AI in education, feedback refers to the offering of information, warnings, and risk indicators to students and teachers based on their learning behaviors. This approach emphasizes the enhancement of performance, personalized support, and the elevation of teaching quality. Effective feedback systems, while taking into account the costs, benefits, and risks of AI, play a pivotal role in the advancement of education (Keller et al., 2019).
Freedom of Choice (FG)	Students should have the freedom to decide for themselves whether they want to be assessed by an AI model or not.
Goal determination (FG)	The goal of the model should be clearly established in advance.
Human-Machine Collaboration (SLR)	In the context of AI in education, human-machine collaboration refers to the collaborative utilization of AI systems in universities to enhance administrative processes, provide support in teaching, and assist existing staff members, while recognizing the importance of human expertise and maintaining a complementary role for AI technology (Keller et al., 2019).
Inclusivity (FG)	A student is more than just the data they produce.
Justice (SLR)	In the context of AI in education, justice refers to the assurance that AI systems generate impartial predictions and decisions devoid of discriminatory factors. This entails addressing potential data misuse, taking into account the desirability of tasks, and integrating ethical principles such as fairness, transparency, and trustworthiness (Keller et al., 2019).

Ethical factors (SLR or FG)	Description
Learning (SLR)	In the context of AI in education, learning refers to the process of acquiring knowledge and skills with the support of artificial intelligence. It involves leveraging AI technologies to enhance communication, production, collaboration, content delivery, assessment, and teacher support, ultimately enabling students to engage in meaningful and effective learning experiences. Quality of learning (Keller et al., 2019; Torres-Rivera et al., 2021).
Mental well-being (SLR)	In the context of AI in education, mental well-being refers to the psychological dimension in IT ethics, which encompasses human behavior, cognition, and emotions in ethical decision-making and technology use. Additionally, social bonding in education and AI pertains to meaningful connections and genuine interactions between individuals (Mâtâ & Boghian, 2019; Tsivitanidou & Ioannou, 2021).
Misuse (SLR)	In the context of AI in education, misuse refers to the unethical use of computer programs or multimedia resources. This misuse encompasses unauthorized utilization, plagiarism, intellectual property violations, and potential threats to human intellect and copyright infringement, with negative implications for individuals, society, and intellectual property rights (Celik, 2023; Mâtâ & Boghian, 2019; Sangapu, 2018).
Open Access Strategy (FG)	Who determines the sharing of a trained model with other universities?
Ownership and Responsibilities (FG)	Who is responsible for what? Data supply, aggregation, processing, storage, communication, etc
Prediction (SLR)	In the context of AI in education, predicting refers to forecasting (final) student outcomes (Keller et al., 2019; Popkhadze, 2021).
Privacy (FG)	It is essential that an AI application handles sensitive data carefully and securely. The data should only be accessible to the students themselves and should not be shared with third parties.
Professional Development (SLR)	In the context of AI in education, professional development refers to initiatives aimed at enhancing skills and knowledge, emphasizing continuous learning to keep up with advancements like AI-based tools. Addressing concerns about job substitution in universities due to AI involves utilizing AI systems in a supportive rather than substitutive manner, which in turn necessitates further training to adapt to new roles (Celik, 2023; Keller et al., 2019; Mâtâ & Boghian, 2019; Sangapu, 2018; Torres-Rivera et al., 2021).
Role of AI (FG)	The AI application should have a supportive role.
Scope of Data Collection (FG)	An AI application can use multiple data points, allowing it to provide advice on more than just study guidance, such as fields of study, internships, or career choices. This can lead to a different perception of students by teachers. Caution is required when

Ethical factors (SLR or FG)	Description
	determining which data is included and which is not, including external sources.
Security (FG)	It is essential that the data and model are not hacked, as this also poses a risk to the integrity of a university.
Teaching (SLR)	In the context of AI in education, teaching refers to the concerns expressed by teachers regarding technical issues and access to software, equipment, audio-video tools, and platforms during teaching. However, teachers also perceive AI as a means to enhance teaching methodology and foster increased student engagement. They emphasize the importance of a balanced and limited use of AI to preserve students' critical thinking abilities (Celik, 2023; Joshi et al., 2021; Keller et al., 2019; Mâtâ & Boghian, 2019; Sangapu, 2018; Torres-Rivera et al., 2021).
Transparency (SLR& FG)	**SLR**: In the context of AI in education, transparency refers to the imperative of openness and lucidity concerning the utilization of data and the decision-making procedures of AI systems. These address ethical apprehensions associated with data misuse and potential risks of discrimination. The evaluation of task desirability on an individual basis and the embodiment of European principles such as fairness, transparency, and trustworthiness assume pivotal roles. The importance of transparent AI decision-making takes center stage, particularly in domains like university admissions (Keller et al., 2019). **FG**: It is important that the basis on which the AI model makes its choices is clear. The university should be able to assess whether the advice a student receives from the AI model is indeed meaningful.
Trust (SLR)	In the context of AI in education, trust refers to the ethical integrity and reliability of systems, taking into account data risks and aligning with European values. It involves evaluating tasks on an individual basis and placing emphasis on principles such as fairness, transparency, and the establishment of trustworthy AI (Keller et al., 2019).
Usability (SLR & FG)	**SLR**: In the context of AI in education, usefulness refers to the growing awareness and acceptance of AI-based tools among teachers, which will drive their increased integration into teaching practices. This integration reflects the recognition of AI's value and the evolving landscape of higher education (Celik, 2023; Gocen & Aydemir, 2021; Joshi et al., 2021; Sangapu, 2018). **FG**: It is important that an AI application is usable for teachers.
Validation (FG)	The models used must be validated for accuracy.
Value of AI (FG)	An AI application can provide insight into the learning process of students, while students can also learn about themselves at the same time.

3.1 Survey

During the second phase of the focus groups, the participants were asked to fill in a survey[1]. The results of the survey (n=15) show a significant skew towards the responses of "strongly agree" or "agree" for all questions. Furthermore, several ethical factors display "strongly agree" scores constituting equal to or exceeding 80% of the responses, namely data (93%), transparency (87%), trust (80%), and explainability (80%). Among the ethical factors, "prediction" exhibits the highest degree of spread along the consideration axis, with a mean (M) of 3.13 and a standard deviation (SD) of 1.51. Examining the ethical factor "teaching," it is observed that the respondents, who are teachers, have responded in a notably neutral manner to the explanation axis (47%), in contrast to their responses to other ethical factors along the same axis. Participant feedback at the survey's end was noted and integrated into a general comments category by the researcher.

3.2 Interviews

The most notable results and contradictions from the interviews about the ethical factors that originated from the focus groups are described in this section, see Table 2. The Roman numerals represent participant IDs.

Table 2: Results and observations from the interviews

Ethical factors	Notable observations
Accuracy	There's a contradiction in how accuracy should be approached, with Participant I advocating for testing AI advice on a small scale, while Participant III questions the definition of accuracy itself. Participant II emphasizes user responsibility for providing accurate information, and Participant IV stresses the importance of accuracy in student assessments.
Auditability vs. Transparency	Participant I stresses continuous monitoring, whereas Participant II is uncertain about auditability and leans towards transparency. Participant IV demands transparency without delving into auditability, showing an inconsistency between the need for auditability and the preference for transparency.
Bias	All participants acknowledge bias but differ in their approaches. Participant I emphasizes minimizing bias through transparency, while Participant II focuses on weighing risks and monitoring

[1] Full results of the survey: https://osf.io/52up4/?view_only=b09296356217455ea491017b7c6418d3

	behaviour. Participant III prioritizes addressing bias and fairness, citing literature, and Participant IV points out the presence of bias in both students and teachers, urging clarity in identifying AI model biases.
Authorization	There's a general agreement on the importance of authorization, but Participant IV introduces a new perspective by linking authorization to competence in teaching without specifying parameters, suggesting a more nuanced view that considers context.
Freedom of Choice	Participants show varied opinions, from Participant I supporting opt-in/opt-out options to Participant IV strongly opposing student control over curriculum or AI assessment. This highlights a contradiction in the level of control and choice students should have.
Goal Determination	While all participants agree on the importance of clear objectives, Participant III introduces a new perspective by suggesting input from a "meta expert" for ethical considerations, indicating a divergence in how goals should be determined and by whom.
Open Access Strategy	Participant I advocates for collaboration and public ownership, while Participant IV is sceptical about the feasibility of idealistic model sharing, pointing to a new perspective in views on how open AI systems should be.
Privacy	There's a general consensus on the importance of privacy and GDPR compliance, but Participant IV suggests non-exclusive access for research, introducing a potential contradiction with the emphasis on data minimization and secure handling.
Transparency	All participants agree on the importance of transparency, but there's a variance in how it's approached. Participant I emphasizes the challenge of AI explainability, while Participant III is skeptical about the transparency facade and the challenges of understanding algorithms.
Value of AI	Participants differ in their views on the value of AI in education, from focusing on administrative tasks and information provision (Participant II) to advocating for students learning from AI (Participant IV). This contradiction reflects differing perspectives on AI's primary role and value in education.

3.2.1 Q-methodology

Figure 3 illustrates how participants positioned the ethical factors from the focus groups on the Q-methodology pyramid from most important to least important. The pyramid shows that most ethical factors are consistently valued similarly by nearly all participants.

Most important | Least important

Participant: I, II, III, IV

3	2	1	0	-1	-2	-3
			Security			
			Validation			
			Validation			
			Scope of data collection			
	Role of AI	Accuracy	Usability	Ownership and responsibilities	Scope of data collection	
	Scope of data collection	Value of AI	Security	Ownership and responsibilities	Open access strategy	
	Transparency	Privacy	Security	Auditability	Open access strategy	
	Accuracy	Privacy	Ownership and responsibilities	Usability	Inclusivity	
Auditability	Goal determination	Freedom of choice	Discretionary authority	Authorization	Transparency	Data origin
Transparency	Bias	Discretionary authority	Authorization	Auditability	Inclusivity	Communication of outcomes
Bias	Role of AI	Inclusivity	Scope of data collection	Goal determination	Ownership and responsibilities	Data origin
Transparency	Bias	Authorization	Data origin	Goal determination	Freedom of choice	Communication of outcomes
Value of AI	Bias	Privacy	Communication of outcomes	Inclusivity	Open access strategy	Validation
Accuracy	Privacy	Role of AI	Usability	Goal determination	Data origin	Freedom of choice
Accuracy	Value of AI	Discretionary authority	Freedom of choice	Usability	Communication of outcomes	Authorization

Figure 3: Q-Methodology results

Source: Own

4 Discussion, Limitations & Outlook

This study sets out to explore the ethical factors influencing the meaningful use of AI in higher education, with a focus on teachers within the Bachelor IT program. The analysis of results from the SLR focus groups, surveys, interviews, and q-methodology highlighted significant differences in the nature and depth of information gathered. The SLR, grounded in scientific articles, provided a broad, global perspective, contrasting sharply with the localized, in detail results captured through focus groups and interviews. This distinction was further seen by the granularity of ethical factors identified. Given this variation, integrating the findings from the different methodologies proved to be complex. The decision to present the research results separately was driven by the realization that combining them would not enhance their value due to the distinct contexts and levels of detail they encompass. This approach ensures transparency in presenting diverse insights into the ethical considerations surrounding AI's integration into education. Acknowledging the potential of AI in education, the study underscores the need for more in-depth, comprehensive research. This call for further investigation is not merely to bridge the gaps identified between the global insights of the SLR and the localized perspectives of the focus groups, surveys, and interviews but also to navigate the complexities of integrating these varied findings into a cohesive understanding of AI's ethical implications in higher education. Also, AI has many different possible application areas in higher education, each possibly with its own unique ethical implications. Future research should acknowledge these application areas and adopt a more detailed approach to AI compared to this study.

There are also some limitations to this study. The systematic literature review faced challenges in search criteria (e.g. the substantial growing volume of publications in the field of artificial intelligence), potentially affecting the initial paper selection, and a single researcher's thematic coding raised concerns about bias. In the focus groups, efforts were made to enhance diversity, acknowledging an inherent lack of complete diversity within the population. The small sample size and exclusive affiliation of participants with one university of applied sciences introduced potential biases, but despite these limitations, the focus group data served as a valuable starting point for further exploration, contributing to the enrichment of the existing identified ethical factors. The recruitment method for interviews raised concerns about confirmation and homophily biases, but a careful selection process aimed to mitigate these biases. The study acknowledged potential biases in the translation process, addressing them through consultation with a senior researcher.

5 Conclusion

In conclusion, addressing the research question of what ethical factors impact the meaningful utilization of future AI technology in higher education, as perceived by teachers within the Dutch bachelor IT program, highlights the need for a holistic approach to understanding the complexities of AI ethics in education, providing a foundation for developing ethical frameworks and informing policy. The study bridges ethics factors and educational technology, advocating for a broader consideration of stakeholder perspectives in AI integration, including teachers and students. This study examines the ethical factors that are relevant for bachelor IT-teachers when implementing AI in education. The results from this study can be used to set up a broad research project that includes the perspectives of all stakeholders to obtain a complete understanding of what AI in higher education will entail. The study's theoretical contributions extend existing knowledge on ethical decision-making in higher education from a lecturer’s perspective by providing a list of ethical factors derived from literature and focus groups.

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