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Regular Article

The acceptability of AI in higher education: A qualitative study about the notion of education and AI

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ABSTRACT

The ethical aspect of artificial intelligence is becoming more pressing. Besides consulting experts, various efforts have been undertaken to consult stakeholders and to understand under which terms the stakeholders consider AI-based systems acceptable. However, reasons in favor of or against AI-based systems in education do not depend solely on questions of usability or functionality, nor on the consideration of moral values. While most studies suggest that privacy and transparency are the main concerns of stakeholders concerning learning platforms and systems, this study indicates that different notions of education might be the reason for considering AI-based systems acceptable in higher education. Semi-standardized interviews were conducted with professors of German universities via video calls. The data was evaluated via "thematic coding." In this qualitative study, we found that the acceptability of AI-based systems in education crucially depends on the participants' conception of education.

1. Introduction

1.1. Context

Even though artificial intelligence (AI) is ubiquitous in media, popular science, culture, and research, it is not clear what AI is. At first glance, it seems that even among experts (philosophers, computer scientists), different notions of AI exist (Hagendorff, 2020, p. 104/105). Furthermore, ethical guidelines in AI ethics have been formulated for various applications and sub-areas; however, they only state deontological frameworks that are ultimately underdetermined in terms of how the rules and guidelines can be implemented, as Hagendorff (2020, p. 112) criticized. As a result, they are not very helpful to developers who work on technical implementation or to the application's users. The ethical use of artificial intelligence and the implementation of values is part of a broader debate not only in AI ethics (Cockelbergh, 2020), guideline development (AI Ethics Impact Group, 2020), policy proposals (High-Level Expert Group on Artificial Intelligence, 2019), but also a significant concern for the general public. The empirical investigation of the attitudes, fears, or hopes of the users (stakeholders), however, is still in the making. There are studies on the ethical background of platforms in the field of "Learning Analytics," e.g. (Howell et al., 2018; Nevaranta et al., 2021), (Okkonen et al., 2020b). However, the acceptability of AI-based systems in higher education has not yet been scrutinized. Acceptance research focuses mainly on issues of functionality and usability. Yet, such studies remain on the factual level. The issues of acceptability, on the other hand, address normative factors. These are either moral factors, such as privacy, transparency, accountability, etc. (values), or non-moral normative factors, such as conceptions of education. This investigation aims to shed light on normative factors from an empirical perspective to understand how the acceptability of AI-based systems in higher education is affected by conceptions of education.

Furthermore, there seems to be a significant discrepancy in the acceptance of AI-based systems. While there is great public outrage about the dangers of AI, when things go wrong, the use of AI-based systems is widely accepted in practice (e.g., in smartphone applications, search engines, etc.). Nevertheless, there are concerns about concrete applications such as "predictive policing" and general concerns introduced into public and scientific discourse by ethicists and scientists. However, little attention has been paid to attitudes based on normative factors apart from the technological context, such as the notion of education. Understanding compatibilities and incompatibilities in attitudes and expectations is a first step toward clarifying strategies that can

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inform recommendations and policy proposals for the successful and ethical implementation of AI-based systems. Incompatible attitudes toward AI-based systems might, for instance, be rooted in educational conceptions. Hence, it might be advisable for universities to consider such educational ideals when implementing learning platforms or chatbots. In particular, it seems plausible that university teachers who have a more competence-based educational ideal might view AI-based systems as more useful compared to colleagues who have a more humanistic educational ideal and perceive the technology as, by their definition, "inhumane."

The proposed approach, based on a qualitative study, has the advantage of allowing the investigation of the acceptability of AI-based systems beyond purely ethical considerations, without merely focusing on functionality and usability (acceptance research). The so-called "Technology Acceptance Model" takes the "perceived usefulness" and the "perceived ease of use" as the "fundamental determinants of user acceptance" (Davis, 1989). Even though the model was extended to take also social influences into consideration (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000), such studies remain on the factual level of user acceptance. This is similar to the methodological approach in "Technology Assessment" (TA), while, on the other hand, the focus in technology ethics is on the normative dimension of acceptance, i.e., acceptability (Grunwald, 1999, 2005; Petermann & Scherz, 2005). Values like privacy or transparency can be hypothesized as determinants that influence user acceptance, whereas those who do not accept the values or do not act in accordance with them can be judged as inconsistent or irrational in their actions (Grunwald, 2005, p. 55). Nevertheless, other determinants beyond technical usability, social factors (acceptance research, TA), and purely ethical factors should be assumed to exist. The difference between (factual) acceptance by the stakeholders and acceptability as possible acceptance must be clarified (Hubig, 2007, p. 163). Hubig distinguishes between weak and acceptability, with the former being characterized as "acceptability" that leaves open the possibility of granting or denying acceptance (Hubig, 2007, p. 148). Strong acceptance is characterized as "justified acceptance." Standards must be established here as to the extent to which damage risks can be accepted. Such criteria are not objective and can only be established through the stakeholders' recognition (Hubig, 2007, p. 106). Implementing an AI-based system in teaching might be optional at a particular university, allowing the faculty to use it or not (weak acceptability). It relies thus on the "caprice" of the faculty. Strong acceptability seeks to understand which normative factors influence the acceptance of a technology. For instance, as proposed here, educational conceptions may influence the use of technology and can be taken as justifying (non-)acceptance.

1.2. Conceptions of education

Here, it is assumed that the user's conception of education is such a non-objective criterion that influences the acceptability of technology in higher education. Hence, it is assumed that the preferences do not rely solely upon the ethical realm. However, other normative reasons should be considered in determining the acceptability of AI-based systems, which are ultimately not ethical in nature. Accordingly, the study sheds light on the acceptability of AI-based systems in higher education based on different notions of education. Specifically, the study is based on the assumption that persons who favor a form of education in the spirit of humanism (in German, *Bildung*) or one based on the Humboldtian model of higher education would be more reluctant to use AI-based systems in higher education. This is assumed because the emphasis of the so-called Humboldtian model of education (Trabandt & Wagner, 2020, p. 68), (Erpenbeck & Heyse, 2021, p. 74) is on the interaction between persons and the autonomous development of the learner. While humanistic education is *process-oriented* (Trabandt & Wagner, 2020, p. 73), *reflexive* (Erpenbeck & Heyse, 2021, p. 74), and *transformative*. (Trabandt & Wagner, 2020, p. 68), competence-based education focuses on "results" (Trabandt & Wagner, 2020, p. 73), i.e., it is *functional/instrumental* and *outcome-oriented*. In such a competence-based model, it might be easier to personalize the learning experience through technology, as it is based on levels of proficiency, allowing AI-based systems to be implemented to achieve specific learning outcomes. Persons who favor a competence-based education model would thus be more likely to consider AI-based systems acceptable in higher education because such systems could be used as tools to reach learning outcomes (Trabandt & Wagner, 2020, p. 73) and acquire the competencies that guarantee certain employability (Tippelt, 2010, p. 260). This development in higher education is mainly part of the so-called "Bologna Process" that aims for a certain comparable standardization.

Although much research has been done regarding the acceptance of Learning Analytics in higher education, where the stakeholders' main concern revolves around privacy issues, it has not yet been sufficiently scrutinized how the notion of education influences the acceptability of AI. Moreover, it has been investigated how a humanistic approach to teaching AI could be fostered (Trifonova et al., 2024) or how prepared teachers are for implementing AI in competence-based education (Fundi et al., 2024). However, the influence of educational ideals on the acceptability of AI has, to our knowledge, not been investigated. Consequently, the research at hand aims to identify stakeholders' notions of education (here, professors at German universities) and relate them to their attitudes towards AI-based systems in higher education. The main focus is on the professors because their educational ideals are likely to be more heterogeneous than those of their students. This is due to the fact that professors might not have been as strongly affected by the "Bologna Process" in their own education as students who have already undergone a more competence-based education. Hence, it is assumed that many professors might still advocate the Humboldtian model and even be familiar with it from their own educational experience.

The benefit of stakeholder surveys or empirical studies, more generally, is that they enable users and developers to discuss mutual expectations in the development phase of an AI-based system. Thus, they leave the possibility of granting or denying acceptance open. Practical ethics, like AI ethics, is not just the application of norms to specific situations or the development of a deontological framework for particular cases. This strategy might be wrongly inferred from the misleading title "applied ethics." However, issues in practical ethics involve the establishment of a discourse that not only represents factual acceptance or approval of the stakeholders. The alignment or reconciliation of mutual expectations is an interaction between persons based on reciprocal relations of recognition. Systems do not have such an ability to recognize someone else as a participant in a discourse. They do not form expectations – unless one uses "expectations" in a more metaphorical way of speaking. They have dispositions that allow them to react to input in a certain way (Hubig, 2020). Users or stakeholders can give or get feedback from the system. However, it is limited to the system's dispositional character, i.e., the range of possibilities the system can react to. Consequently, acceptance studies cannot just be about the interaction of the users with the already implemented and "finished" system. Instead, they have to be part of the development process, where users' expectations align with developers' ideas and expectations.

2. Related work

The use of AI-based systems or platforms in higher education is rapidly growing. Some applications can be found under the heading of "smart classrooms" to increase attention and motivation through the implementation of smart devices in the environment of the learner (see, e.g. (Jia et al., 2020; Liu & Peng, 2021)). Various applications were developed using natural language processing to evaluate texts (Litman, 2016, pp. 4170–4176) or chatbots as tutors (Afzal et al., 2019). Also, so-called "social robots" are used for different learning purposes (see for an overview (van der Berghe et al., 2019)). Recent studies have reviewed the literature on AI-driven Learning Analytics (Alfredo et al., 2024; Ouyang & Zhang, 2024) or the impact of Generative AI on it

(Yan et al., 2024, pp. 101–111). Nevertheless, ethical concerns or normative factors have not been raised directly under these headings, and only a few ethical issues have been tackled regarding learning platforms. For instance, a value like “trustworthiness” “is less represented in the current research.” (Alfredo et al., 2024) Bogina et al., for example, discussed the education of stakeholders in the “areas of algorithmic fairness, accountability, transparency, and ethics (FATE)” (Bogina et al., 2021), but this is a theoretical investigation rather than a study involving stakeholders. In contrast, Latham and Goltz conducted a survey “taken of attendees at a national science festival event,” where “most participants (77%) were worried about the use of their data” (Latham & Goltz, 2019).

2.1. Learning analytics

Furthermore, studies in the field of “Learning Analytics” have been conducted. Learning Analytics is based on the use of big data that is collected, analyzed, and reported to optimize learning (Howell et al., 2018; Siemens, 2013). While there is more research on students' attitudes, academics' views are still underrepresented (Howell et al., 2018, p. 2). Howell et al. (2018) conducted a qualitative study to analyze academics’ concerns and attitudes thematically. The study showed that ethical issues are important for academics in developing and applying learning analytics (Howell et al., 2018, p. 14/15).

Okkonen et al. divided the literature about learning analytics into two “trends” (“positivistic and critical”). While the former is focused more on the technical aspect, the latter tries to integrate “ethics of using data as well as discussion of privacy and agency.” (Okkonen et al., 2020a, p. 78) The findings of their study among students and staff at various universities in Finland were that students’ “ethical considerations” mainly are grouped around “transparency,” which refers according to them to the usage of data either “for the benefit of the students and using the data without hidden agenda” or to the “misusage of data,” and “using sensitive and personal data.” (Okkonen et al., 2020a, p. 83) The issues that are mainly addressed are, in the end, how to handle the data (Okkonen et al., 2020b). This finding is consistent with other studies involving stakeholders, particularly students who raise such concerns (Sun et al., 2019, p. 10).

Also, Nevaranta et al. identified data handling and data privacy as the primary ethical concerns. They conducted two studies: one before the pandemic and one during the pandemic (Nevaranta et al., 2021, p. 3/4). Although they state that the students “have stronger opinions about […] ethical usage of their own data”, the survey statements are largely within a legal framework (cf. the item: “Institution should follow laws and regulations to keep my data safe.”) (Nevaranta et al., 2021, p. 10/11). Such statements represent more issues of awareness than they reflect ethical issues. The talk of “benefit” (Nevaranta et al., 2021, p. 10/11) for the institution to collect data should also be specified more. Otherwise, it is too ambiguous because it could be, for instance, for economic or academic benefit, as well as for research or the improvement of teaching or administrative processes. Furthermore, in the open questions they posed, the students' main ethical concern was data privacy (Nevaranta et al., 2021, pp. 11-14). Ifenthaler and Schumacher conducted a quantitative “laboratory study” examining students' expectations about learning analytics. They primarily addressed data privacy issues in the study (Ifenthaler & Schumacher, 2016). Pargman and McGrath did a literature review to map the ethical aspects of learning analytics found in empirical studies. The methods of the examined studies were “surveys, case studies, experimental studies, mixed methods, and grounded theory.” The main ethical aspects also included “transparency” and “privacy” when analyzing the students’ data. The “types of stakeholders involved” in the studies were mainly students (36%) and academics (39%) (Pargman & McGrath, 2021).

2.2. Guidelines and conceptual frameworks

In addition to empirical studies, guidelines, conceptual frameworks, and challenges were developed by (Drachsler & Greller, 2016, pp. 89–98; Ferguson et al., 2016; Pardo & Siemens, 2014). According to Pargman and McGrath, issues, such as “transparency, privacy, and informed consent” mainly match empirical studies (Pargman & McGrath, 2021, p. 11). Ferguson et al. identified several “challenges with ethical dimensions” for learning analytics, which mainly revolve around data protection and privacy (Ferguson et al., 2016). Drachsler and Geller abstractly described the “fears towards learning analytics” without referencing empirical studies. They stated that “concerns,” “arguments,” and “critical topics” were “collected from participants” of a “workshop series” about ethics and privacy. They want to establish a conceptual framework that, besides legal aspects, also provides “ethical foundations” drawn from “research ethics” and, more specifically, biomedical ethics (Drachsler & Greller, 2016, pp. 91-94). According to them, “projects should follow a value-sensitive design process” by adopting the “DELICATE checklist” (“determination,” “explain,” “legitimate,” “involve,” “consent,” “anonymise,” “technical,” “external”), which “is derived from the intensive study of the legal texts […], a thorough literature review and several workshops with experts” (Drachsler & Greller, 2016, p. 96).

Pardo and Siemens discussed in their theoretical or conceptual study the ethical dimension of Learning Analytics, also mainly concerning privacy, where, for example, transparency and accountability are described as “issues derived from privacy.” (Pardo & Siemens, 2014, p. 448) As a result, the primary concern of the theoretical and empirical studies, which reflect the concerns of experts or stakeholders, is privacy. However, the participants in the present study raised only a minor concern about this issue. This might be due to the nature of Learning Analytics, which mainly focuses on the collection and analysis of data and might thus evoke concerns about privacy issues.

2.3. Acceptability – ethical aspects

Ethical Aspects are employed within the scope of some studies (Howell et al., 2018; Ifenthaler & Schumacher, 2016; Nevaranta et al., 2021), (Okkonen et al., 2020a, p. 85), but the conceptual level has not been scrutinized sufficiently by discussing the concept of “acceptability”. Although there have been attempts to develop the framework conceptually (Drachsler & Greller, 2016, pp. 89–98; Ferguson et al., 2016; Pardo & Siemens, 2014), empirical studies need to sustain and complement such a framework. Furthermore, ethical or normative factors that go beyond privacy issues need to be emphasized, as these issues fall mainly within the legal domain. Investigations about learning platforms focus mainly on the pedagogical background (Röpke et al., 2018). However, normative aspects, like educational ideals, for implementing learning platforms have not yet been thoroughly scrutinized or investigated on a conceptual level, nor investigated on an empirical level. Marras et al., for example, only discuss the issues of “fairness” and “equality” of learning platforms on a conceptual level, but not empirically (Marras et al., 2021).

The studies above remain in the traditional form of acceptance studies, investigating which values are essential for the stakeholders. However, if one assumes these values to be ultimate or proper interests or expectations in a hypothetical form, the stakeholders would have to agree on whether the platform complies with data privacy laws. It is, of course, the case that values like transparency, personal data privacy, etc., are primarily and, to a large extent, desirable. However, these hypothetical situations merely assume ultimate or proper interests. Users want their data to be anonymous and treated confidentially, *but* they also publish it on social networks. This is because the “acceptance levels of the users are often irrational and contradictory.” (Hubig, 2007, p. 19) Therefore, when forming hypotheses and developing the research question, the ultimate or proper interests are often queried, but discrepancies that show contradictory or "irrational" acceptance levels are not carved out. By taking discrepancies as a starting point, one can ask for the reasons, i.e., why a technical system is rejected or accepted, and first and foremost, open up a search space for such reasons. It must be examined which reasons the users have (implicitly or explicitly) and which causes guide the behavior beyond assumed noble interests or practical constraints.

Here, qualitative and quantitative studies can add value to ethics that ethicists cannot achieve in an armchair. However, hypothetical conditionals cannot be the outcome of an acceptance study, e.g., "If the privacy of the user were protected, the stakeholders would accept such a system." However, the *hypothetical* conditional does not test why stakeholders might then *actually* not accept such a system, although all (ethical and legal) regulations are followed. In a way, we all want "morally good" systems and would like to have values implemented in them. However, the causes, reasons, and circumstances that might, in the end, interfere with the hypothetical and desirable situation are not investigated.

Consequently, more research is needed because the focus of the empirical findings on questions of privacy might be one-sided and not the sole or even primary reason for the non-acceptance of AI-based systems or platforms in higher education. While there is a strong focus on the issue of privacy, AI-based systems (like a learning platform) might evoke other concerns because of the specific connotations that the stakeholder might have under the umbrella term AI. Thus, more research might be helpful because, as described above, different conceptions of AI lead to different ethical assumptions (superintelligence vs. applications of weak AI). Such differences might also be present in the stakeholders' conceptions (instructors and students). A qualitative research approach is needed to determine different notions of ethical concerns, pedagogical aspects, and AI to identify and categorize the statements. This will lead to the opportunity to identify (co-)relations and incompatibilities of statements. The benefits of the research are to analyze and synthesize concerns beyond privacy issues and elaborate suggestions on how the concerns – in the case that they are not fundamental and rest on empirical premises (Schönmann & Uhl, 2023) – can be confronted to improve the acceptance of AI-based learning systems.

3. Research question and hypothesis

3.1. Research question

Is there, thus, a connection between the notion of education and the acceptability of AI in higher education? Furthermore, potential confounders, e.g., a general aversion toward technology, must be considered. In this study, the participants were asked about their use of technology in their classes and lectures, and their willingness to learn new ways of teaching supported by technology. It was found that all stated that they use technology frequently in their classes and are willing to learn how to implement technology in their classes.

3.2. Hypothesis

It is hypothesized that an interaction-based and humanistic notion of education comes along with attitudes that tend to reject AI-based systems in higher education. In contrast, a functionalistic and competence-based understanding of education tends to lead to attitudes that consider such systems acceptable. It seems at least plausible, since a functional definition of AI as a tool could also be more easily coupled with the latter educational concept. Hence, it is assumed that if one holds the view of a more humanistic idea of education, one is more reluctant to use AI-based systems in higher education. In comparison, one who holds the view of a competence-based model of education will be more inclined to accept AI-based systems in higher education. This hypothesis serves as an interpretative lens for analyzing the data and frames it against the backdrop of educational theories and ideals to explain differing attitudes toward the acceptance of AI in education.

4. Methodology – study design

The study is exploratory, so a qualitative research method seems best, as it can help identify different notions underlying crucial concepts. The exploratory and open nature of the topic requires empirical grounding, as relying solely on ethicists' expertise to understand stakeholders' (students, instructors, and developers) ethical concerns is inappropriate. However, the ethical concerns of the experts are taken as a preliminary benchmark of the stakeholders' concerns. It might be that a shift is necessary, whereby stakeholders' concerns will need to be taken as a new ethical benchmark for the development of AI-based systems. The concerns of the stakeholders cannot just be wiped away by other or "more" important concerns from experts. Qualitative research is based on the so-called "Thomas Theorem": If something is defined as real (the concerns of the stakeholders), then it is also "real in its consequences" (Flick, 2014, p. 82). Here, the real or even actual consequence might be that the systems are not accepted or used. So, for example, if someone fears AI because of privacy concerns, even though she has no reason to, she might still choose not to adopt it, i.e., her fear is real and has consequences.

4.1. Data collection

We collected data through interviews with stakeholders. Regarding the acceptance of learning platforms, teachers and learners are the stakeholders. We chose university teachers because the students might already have been influenced by competence-based education through studying after implementing the Bologna process. Here, the focus was on university teachers (full professors) from three universities in Bavaria. We selected subjects from different disciplines (Humanities, Social, Natural, and Computer Sciences) to examine whether their backgrounds influence their attitudes toward AI-based systems. Due to the study's exploratory nature, a small sample ($n = 11$) from three universities in Germany and six different faculties (Management, Engineering, Natural Sciences, Theology, Humanities, and Social Sciences) was selected. It is a "nonprobability" sample and a mixture of "convenience" and "purposive sampling." (Lune & Berg, 2017, p. 38/39) The average age of the participants was 42.4 years. Six male professors and five female professors participated in the study. The subjects were interviewed via video call. We conducted the interviews in German and transcribed and anonymized them. They lasted 10 to 15 min (The authors translated parts of the transcript for the paper.) The form of the interviews was semi-standardized. The advantage of such non- or semi-standardized interviews is that they allow for the analysis of concepts and understanding of the world from the participants' perspective (Lune & Berg, 2017, p. 70). This also had the advantage of allowing for more spontaneous responses than e-mail interviews.

4.2. Data analysis

After the transcripts were created and read for a first overview, codes were generated from the interview questions. The questions concerned the conception of education, the use of technology in the classroom, training in technology use in the classroom, the conception of AI in general, and AI in teaching. The transcripts were then coded. The coding showed that the conceptions of education also appeared in the use of technology and AI in teaching. Hence, the conceptions of education were examined further and could ultimately be categorized into humanistic and competence-based conceptions. This differentiation was also found in the literature and the teaching philosophies of universities. Thematic analysis has the strength that themes can be developed inductively from the data and not deductively from established theoretical frameworks, thereby avoiding the interpretation of the data being constricted by the given theoretical framework from the outset.

However, we were also able to base the themes about education in the literature on educational conceptions. We chose thematic analysis due to the explorative nature of our research to understand the relationship between education and AI, particularly its acceptance in teaching. This is also why we did not use grounded theory because, although it is similar in approach, it requires a theory to emerge, which did not align with our research goals. Due to the exploratory nature and the limited sample size, developing a theory from the study was dismissed.[1] Certain limitations of this study method could be addressed in future research. For example, further qualitative research could be grounded in a theoretical background, and quantitative studies could provide more robust findings for establishing the connection between the acceptability of AI and educational conceptions.

The data was evaluated via "thematic coding" (Flick, 2014, pp. 424-428), (Lune & Berg, 2017, p. 184). The coding is thus "grounded" in the empirical material and leads to comparable concepts and categories (Flick, 2014, pp. 398, 404). This "inductive" method allows a certain "generalizability" of the results to be obtained. (Flick, 2014, pp. 114, 398, 495), (Lune & Berg, 2017, p. 188) However, purposive sampling can have a limitation regarding generalizability (Lune & Berg, 2017, p. 39). The interviews were thematically divided into three major categories: notions about education and teaching, use of technology, and general ideas about AI, including its use in higher education teaching. The second topic was chosen to exclude a general aversion toward technology. The study's findings are also consolidated in relation to a conceptual background from pedagogical theories (see discussion section). This means that triangulation is achieved to strengthen the findings. Triangulation can be achieved by combining qualitative and quantitative methods or within qualitative research by combining "different kinds of data," using different methods, or by combining theories with empirical findings (Lune & Berg, 2017, p. 14/15), (Flick, 2014, pp. 182-191), (Denzin, 2010). The latter form of triangulation is used to substantiate educational concepts.

5. Findings

A general aversion toward technology could be excluded because almost all participants stated that they use it frequently in their daily lives and in their teaching. The latter might be due to the challenges during the pandemic and the change to online classes. In general, they also expressed openness to using new technology in their classes, and all obtained their knowledge autodidactically via books, tutorials, or "learning by doing." The sample was too small to draw conclusions about the differences based on the participants' disciplines. However, it might have some influence, as a study by Flick about technology in general has shown. The use of technology is described against the background of an "ideal-typical distribution" and specified in three case groups (computer scientists, social scientists, and teachers) (Flick, 1995, pp. 123-126). This distribution is also reflected in early childhood encounters with technology via retrospective anchoring: computer scientists used technology more playfully and successfully, social scientists faced mostly failures with a device, and teachers experienced technology passively (Flick, 1995, pp. 173-178). There are group-specific differences in the perception of and dealing with technology and ideas about technological change. However, according to Flick, the findings need to be further developed through a representative survey since this is an exploratory study (Flick, 1995, p. 284). However, the analysis of the transcriptions indicates that the perception of technology and AI lies across the disciplines and is anchored in the educational concept.

All participants demonstrated basic knowledge of AI and described it using keywords such as "deep learning," "machine learning," "algorithms," or "pattern recognition." No fear or concern about any superintelligence was mentioned. Some also knew about possible applications of AI-based systems in higher education but have not used such systems in their classes. Despite the mentioned similarities, the identified thematic domains allowed us to distinguish two groups. Some described education as the acquisition of *competencies* to fulfill learning *goals*, while others viewed education as based on *interactions* between persons. Those exchanges should then lead to a *transformation* of the learner. The participants who were more open to using AI-based systems in higher education explained education as a development of competencies. The participants who were more reluctant to use such systems explained education as process-related or transformative. The competence-based model of education is also more matched with keywords such as "skills," "designing the environment," and "effective transfer of knowledge." At the same time, a participant of the other group stated that "knowledge transfer" does not really count as education. An interaction-based view of education is associated with humanistic ideals like "free development," "intrinsic motivation," and a "transformation of the self and world relation." Also, Humboldt was explicitly mentioned by one participant as a reference. Other vital aspects were "social exchange" and "learning together." These ideas also inform the refusal of AI-based systems: one participant remarked that problems are solved by people interacting with each other. We derived statements from the manuscripts summarizing educational conceptions and the use of AI in teaching, with respect to department affiliation (see Table 1). Humanistic conceptions of education seem present across different disciplines (ranging from the humanities to the natural sciences).

Even though AI-based systems are seen as helpful when obtaining basic knowledge, most participants of the second group believe that such systems might not be helpful in developing reflection and asking questions. However, it was stated that AI-based systems might be used as an "instrument" or to "illustrate things." It also needs to be considered that

Table 1
The statements represent analytical generalizations derived from thematic analysis of the data from the transcripts, not direct quotations. The table aims to summarize the transcripts and to serve as a processed source.

	Education is …	AI in teaching …
Business School (3 participants)	… knowledge, skills, and to build competencies. … an effective transfer of knowledge.	… is already used in the degree program. … can help and be a relief.
Engineering and Mathematics (2 participants)	… human culture, the basis for living together. … about an understanding of the world and cultural goods.	… does not help to solve problems because interaction is needed. … will not work because the data sets are too small to train them well. It is easier to talk to people.
Humanities and Theology (2 participants)	… giving opportunities to develop and human contact. … to enable orientation in personal and professional contexts.	… will not lead far, but could be a specific instrument. … will not be helpful because deliberation and argumentation are needed.
Social sciences (2 participants)	… the transformation of the self and world relation and social exchange. … exchange and to learn something together.	… in sociology, it is rather difficult to use because it is more about asking questions. … is not constructive and far away. Important is the imparting person.
Linguistics (2 participants)	… not about specialized knowledge. … the development of the personality to the full extent in the sense of Humboldt.	… might help to illustrate and for basic knowledge, but what goes beyond is too complex. … has often biased prognoses. Might reinforce the focus on declarative knowledge.

[1] Furthermore, we used a bottom-up strategy for the conception of AI. Rather than theorizing about it or presenting the participants with examples, we let them develop their own conception that adapts to their educational needs or concerns about AI. (We are thankful to an anonymous reviewer who pointed this issue out.)

some are reluctant to use AI-based systems because (1) they do not know how such systems might be used successfully, (2) the development is far away, and (3) high effort is involved to employ the systems.

In Figs. 1 and 2, we show the connection between ideas of competence-based education and humanistic education, on the one hand, and positive or negative connotations of AI in more depth. We extracted keywords and sentences linked to educational ideas and attitudes toward AI from the transcripts and visualized them as word clouds to demonstrate the connections. Concepts mentioned more often (such as “tool”) appear bigger in the figures. Since reservations often need more context to mark them as negative, we decided to use longer strings of words to show the meaning more clearly. Overall, 107 statements were extracted. Fig. 1 is composed of 30 statements (20 about competence-based education and 10 about potential usages). Fig. 2 is composed of 77 statements (43 about education and 34 about reservations toward AI in teaching).

The study was conducted before the advent of large language models for chatbots, such as ChatGPT. Hence, the participants did not use AI-based systems and were more skeptical that certain forms of feedback or personalization were possible than might be the case after tools like ChatGPT became ubiquitous. However, almost all used technology for teaching, such as learning platforms, tools for surveys during class, or collaborative writing.

6. Discussion

It seems that technology usage in the classroom started or intensified during the pandemic, and the implementation of online classes for participants. The adoption of technology was primarily achieved autodidactically or through exchanges with peers. Workshops about technology in teaching were rarely taken. It cannot be inferred whether a few workshops were offered or not taken due to personal reservations against them. Since almost all learned about technology integration without their universities' guidance through workshops, it seems that the benefits of particular tools depend primarily on personal beliefs regarding their usefulness for one's teaching style. For instance, one participant described creating exercises or tracking learning progress as useful. These applications resonate more with the participant's competence-based educational conception. Another participant mentioned using collaborative writing tools in which students interact

Fig. 1. Ideas of competence-based education and positive attitudes toward AI in teaching, including potential usages

Note: We took the key concepts of competence-based education from transcripts of three participants who mainly expressed their idea of education under the topic of acquiring competencies (green). Those participants also showed more positive attitudes toward AI in teaching and were more open to possible implementations of AI in teaching (blue).

Fig. 2. Ideas of humanistic education and reservations against AI in teaching

Note: In light green are key concepts/sentences mentioned regarding a humanistic conception of education from the transcripts of eight participants. In the other color, the reservations against AI in teaching are shown.

and develop an argument or text together. This resonates more with the participant's humanistic educational conception.

We asked whether there is a connection between the notion of education and the acceptability of AI in higher education. Our findings suggest that how AI-based systems are envisioned to be integrated into teaching depends on the conception of education. The distinction between a competence-based and a humanistic conception of education is present in the literature. However, they have not been developed thoroughly as conflicting ideals. To base our findings on the literature about pedagogy and education, a further discussion of the distinction must be undertaken to clarify its oppositional character.

The interviews were conducted in German. In this paper, “education” has been used to translate the German word “Bildung.” It could also be translated as “formation,” but “Bildung” is a word with no equivalent in other languages, such as English or Spanish (Gudjons & Traub, 2016; Raithel et al., 2009). It has been observed that participants favor either a more humanistic or a more competence-based educational model. To support this distinction, it needs to be embedded in discussions grounded in educational theory and pedagogy. For this purpose, German literature is used mainly since the concept of “Bildung” is German, and it would be difficult to distill it from English literature. This relation to pedagogical theories will lead to a more fine-grained distinction and strengthen the findings through triangulation. Although competence-based education is discussed under the heading of “Bildung” (Raithel et al., 2009, S. 36-45), (Trabandt & Wagner, 2020, pp. 65-75), it can also be distinguished as a different approach toward education. It seems that competence-based education primarily has its roots in professional training in the USA, the UK, Canada, and Australia, and has also been adopted in developing countries for professional training because it allows the formulation of learning outcomes, outputs, and content tailored to the needs of professional practice (Tippelt, 2010, p. 260). Several universities have adopted, developed, and implemented a competence-based approach to their educational models in recent years, with different central focuses. (Aalborg University, 2015; Tecnológico de Monterrey, 2018), (University of Twente, n.d)

The focus of competence-based education is on the “results” (Trabandt & Wagner, 2020, p. 73), while the humanistic education is process-related (Trabandt & Wagner, 2020, p. 73) and reflexive (Erpenbeck & Heyse, 2021, p. 74). It is described as a learner's free development to understand the world and oneself comprehensively (Trabandt & Wagner, 2020, p. 68). Hans-Christoph Koller describes education also as process-related and specifically as a "transformation of the world- and self-relation." Although his conception is rooted in a more Humboldtian educational model, it transcends this model by not focusing on the development of forces or dispositions but by focusing on the process initiated by "failure or a critical event" (Koller, 2018, p. 16). However, the primary source for a humanistic, transformative, and process-related educational model is Humboldt and the "New Humanism" movement (Koller, 2009, pp. 74-76). Another source is Immanuel Kant, who sees the development of free and autonomous subjects as a primary task in education within the movement of "Enlightenment." (Kant, 1923) The competence-based model stems more from a constructivist tradition (see, e.g. (Piaget, 2015; Vygotsky, 2012),), although overlapping characteristics can be identified.

The humanistic educational model is *process-oriented* and *transformative*, while the competence-based model is *functional/instrumental* and *outcome-oriented*. In the first model, education is understood as an end in itself; in the second model, education is a *means* to an external end: either to meet a learning goal or acquire competence. Both models have advantages turned into disadvantages when attacked by the opponent's view. In the competence-based model, it might be possible to personalize the learning experience and make it practice-oriented (Hericks & Rieckmann, 2018, p. 258). Furthermore, such a model might provide better measurement standards by formulating proficiency levels. However, this can also be considered a disadvantage because not everything in an educational process might be quantifiable or measurable (Trabandt & Wagner, 2020, pp. 68, 75). A competence-based model might convert the learner's autonomy into competence in organizing and assessing one's own output in the light of given goals and tasks (Erpenbeck & Heyse, 2021, p. 75). Consequently, the learner might be able to regulate her behavior to obtain a given goal but not be able to set her own goals, thus not acting and thinking autonomously. Additionally, focusing on learning outputs and outcomes can be seen as reducing education to (economically) utilizable practices without considering one's role in society and its ethical implications (Trabandt & Wagner, 2020, p. 67). By contrast, a humanistic education (as it is offered, e.g., by liberal arts colleges) might be considered as too general or even counterproductive in the free market. Our findings contribute to educational theorizing by addressing the acceptability of AI applications in education. It seems to us that, so far, technological tools have not been actively linked to educational ideals or to how they affect their adoption and use. The present study, therefore, bridges a gap between pedagogy and technology acceptance (see also Section 7.1).

7. Conclusion

The concepts and ideas about education from the empirical findings coincide with the conceptual background of the pedagogical theories. The pedagogical framework supports the distinction drawn between a functional and a humanistic concept of education. Consequently, the generalized conceptual distinction can be used to explain the acceptability of AI-based systems in higher education. If one advocates a more humanistic idea of education, one will also be reluctant to use AI-based systems in higher education. Moreover, if a competence-based model of education is held as a view, then AI-based systems in higher education are generally accepted by this person. The study, therefore, seems to demonstrate a connection between the notion of education and the acceptance of AI-based systems in higher education. This indicates that there should be a change in the understanding of how AI-based systems are perceived and which reasons are preeminent for accepting such systems. Much work remains to be done in the intersection of computer science, pedagogy, and social sciences before a complete understanding of the acceptability of AI-based systems can be established.

7.1. AI acceptance model in education

A methodological consequence of the proposed approach is that it is possible to request reasons for acceptance and refusal that are not directly related to technological issues or ethical concerns. Querying the proper or ultimate interests of stakeholders alone does not explain discrepancies in acceptance levels, as it remains in a hypothetical realm without considering other reasons. Furthermore, the proposed approach for study designs opens up a possible search space for testing other variables in further qualitative or quantitative studies. Beyond the methodological contribution to acceptance research, our study's results are significant because they address the gap between pedagogy and technology acceptance, particularly amid the rise of AI and new possibilities in education. So far, the background of educational theories has been neglected in discussions of AI adoption. This study contributes to a better understanding of educational theorizing by addressing the acceptability of AI applications in education. The implications of our results are summarized in the AI acceptance model for education (see Fig. 3).

It has the potential to establish a new framework for conducting acceptance research on technological innovation in education and also has practical implications for various stakeholders (see Section 7.2).

7.2. Recommendations for various stakeholder groups

If, as the present study suggests, educational concepts and acceptance levels of AI-based systems are connected, then research is needed to further explore this to improve AI-based systems in education and increase their acceptance levels. It might be possible to link certain educational concepts to specific technological applications, or to develop systems that more closely resemble those concepts to increase acceptance of such systems. Participants who adhere to a humanistic notion of education saw technology as assisting the interaction with the learners (audio-visual preparation for the lecture, for example). Technology and AI are understood as *means* but not as adequate or promising for a free development process. In contrast, the idea of "AI as a tool" can more easily dock with a functional or instrumental concept of education. This implies that more work is needed to connect AI-based systems with humanistic educational ideas.

Our findings have practical implications for various stakeholders. University leaders should integrate their vision for AI into their mission statements and strategy papers, aligning AI with their respective educational ideals. For institutions, it is crucial to understand that their teaching staff may be more or less open to using AI technologies in teaching, depending on their respective educational ideals. The AI acceptance model in education can serve as a catalyst for discussion within institutions to, on the one hand, sharpen their mission statements in teaching and, on the other hand, develop strategies that facilitate the use of AI across oppositional views about the purpose of education.

The AI acceptance model for education, illustrated in Fig. 3, may guide higher education institutions in implementing AI-based systems more effectively. In practice, institutions should begin by assessing the educational ideals prevalent among their faculty through surveys or focus groups to identify whether their faculty leans toward humanistic or competence-based conceptions of education. Based on this assessment, institutions can then tailor AI tool selection and training accordingly. For competence-oriented faculty, tools that support personalized learning paths and measurable outcomes should be promoted. For humanistically oriented faculty, tools that facilitate dialogue, critical reflection, and collaborative learning should be promoted. Institutions should involve stakeholders, i.e., faculty, students, and administrative staff, early in the design and implementation process through participatory workshops to align AI applications with diverse educational ideals and to proactively address concerns. Developers can use the framework to design customizable AI systems. These may accommodate different pedagogical approaches to ensure broader acceptance.

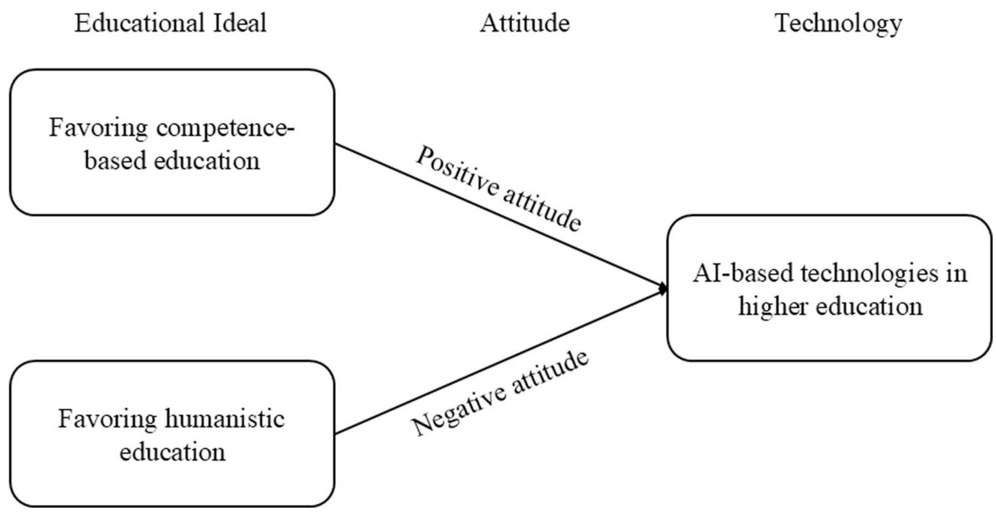

Fig. 3. AI acceptance model for education.

Moreover, policymakers may integrate educational ideals into funding criteria to encourage the development of AI tools that serve multiple educational philosophies rather than a one-size-fits-all approach. This might lead to research and development that fosters AI applications for different educational ideals, without neglecting any of them. This might also facilitate critical thinking and judgment in the use of AI tools, which are not merely tools to nudge students toward learning objectives but also contribute to a broader concept of education as *Bildung*. Students should be enabled to reflect on their educational ideals and on how different universities might help them use AI critically by aligning with those ideals.

7.3. Limitations

The study is subject to several limitations, two of which are particularly important and will be mentioned here. The first limitation concerns the number of participants, which was too small to make assumptions about differences regarding the participants' disciplines and to generalize the findings further. Further research with more participants from different disciplines might also shed light on the impact of the background of participants on AI acceptability. A second potential limitation is that the study group comprises only university professors who might have an occupation-specific view on the issue. This limitation could be addressed in future research by expanding the surveyed group of stakeholders to include, for instance, high school teachers.

The acceptability of AI in higher education

A Qualitative Study about the Notion of Education and AI.

Data availability statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Ethics statement

Approval for the project's studies was granted by the German Association for Experimental Economic Research (GfeW). Certificate No.: D8BPNocs (24.05.2023). The research adhered to the Declaration of Helsinki, and all participants consented freely and in writing to participate.

Generative AI statement

No generative AI tools were used during the preparation of the manuscript.

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CRediT authorship contribution statement

Florian Richter: Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Matthias Uhl:** Conceptualization, Investigation, Methodology, Project administration, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssaho.2026.103207.

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