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University teachers' perceptions of responsibility and artificial intelligence in higher education - An experimental philosophical study

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ABSTRACT

This study investigates university teachers' relationships with emerging technologies by focusing on the uptake of artificial intelligence in higher education practices. We utilise an experimental philosophy approach to i) determine university teachers' intuitions around universities' responsibilities to adopt new artificial intelligence technologies, ii) understand the conditions under which university teachers consider artificial intelligence defensible and, hence, would be willing to introduce such tools and services into their daily practice and iii) specify teachers' self-reported knowledge of artificial intelligence. An online survey, where participants were sent one of three different cases (Case A related to first-generation students, Case B, an archetypical student, Case C, students with a learning disability), and 18 identical questions across all three cases. The survey was distributed among 1773 teachers. Based on the responses of 194 university teachers, we identify differences related to responsibility, equity, and knowledge about artificial intelligence. Our quantitative data exhibited that in Case A and Case C, the respondents ranked to a higher degree that universities should use artificial intelligence tools and systems to achieve equitable outcomes. Data revealed no statistically significant associations among the respondents with regard to background variables in Case A. However, Case B and Case C disclosed statistically significant associations concerning gender, age, faculty, and academic position among the participants. Moreover, we identify teachers' fears and scepticism about artificial intelligence in higher education, concerns about fairness and responsibility, and lack of knowledge about artificial intelligence and resources to engage with artificial intelligence in teaching practices.

1. Introduction

Universities play a crucial role in society through their research and innovation, and by transforming research insights into value (Buzzelli & Asafo-Adjei, 2022; Krücken, 2003). However, research suggests that universities are slow to adopt new techniques, research and technologies to improve their teaching and learning practices (Liu et al., 2020; McGrath et al., 2017, 2019; Prinsloo & Slade, 2017). This resistance to change in higher education has institutional, cultural, economic, political, cultural, and contextual explanations (Liu et al., 2020), and changing practices also involves renegotiation of the complex relationship between emerging technologies and institutional traditions of teaching and learning (Säljö, 2010).

This paper investigates university teachers' attitudes to emerging technologies by examining their intuitions on the adoption of artificial intelligence (AI) in higher education. Artificial intelligence is making rapid advances in all areas of society, and is expected to play a major role in education in the near future (Carvalho et al., 2022). This study seeks to understand what would make university teachers willing to change their practices and integrate AI into their teaching. Teachers' attitudes are important as teachers can act as conduits for change in higher education and for the translation of policy into practice (McGrath et al., 2017). The study focuses on responsibility and equity in the education sector, but unlike previous work (Chounta et al., 2022) it specifically targets higher education. It is guided by normative research questions about who should benefit from AI technologies in higher education (AIED), and how they should be deployed. This study seeks to address a research gap in the work on AIED in this journal, as well as ethical

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concerns over the increasing global deployment of AIED and university teachers' generally low AI literacy (Luckin et al., 2022; Laupichler et al., 2022). It also echoes recent efforts on social justice in learning analytics (Holstein & Doroudi, 2022; Williamson & Kizilcec, 2022; Wise et al., 2021) and educational technology (Cerratto Pargman et al., 2023).

The first section of the paper examines university teachers' uptake of new technologies, and introduces path dependency as a conceptual anchor to frame the argument that universities experience inertia towards socio-technical change. In the second section, the focus of the work on educational innovation is situated by illustrating how AI is entering the higher education sector. The third section considers whether universities embracing AI in their practices are obliged to act – particularly in light of the massive amounts of data on student performance that universities using AI have access to. The fourth section describes the experimental philosophical method, before reporting the findings and discussion. The paper then concludes with some suggestions for future research.

1.1. Technology uptake and institutionalised path dependency

An overview of the literature on university teachers' uptake of technology highlights several independent and related themes that explain resistance to changing practices and adopting new technologies (Liu et al., 2020). These themes include *ease of adoption*, where new tools need to be easy to incorporate (Chan et al., 2016), *research prioritisation*, where academics prioritise their research over introducing new practices to their teaching (MacKeogh & Fox, 2009), *the importance of culture and context* (Stensaker et al., 2007), the implications for social activities in education as already discussed (Säljö, 2010), and teacher preferences (Luckin et al., 2022).

In this paper, the concept of path dependency is used as an overarching concept to frame the argument that universities experience inertia towards socio-technical change. Path dependency in this paper is characterised by three factors: i) the collective nature of work practices, which suggests that organisations tend to institutionalise and reinforce their practices (Misra, 2020; Pierson, 2000; Schreyögg et al., 2011; Sydow et al., 2009); ii) the institutional density of politics, which suggests that, as social actors make commitments based on existing institutions and policies, the cost of exiting from them rises dramatically (Buzzelli & Asafo-Adjei, 2022; Pierson, 2000); and iii) political authority and power asymmetries, whereby state-subsidised universities face little competition and therefore resist change (Misra, 2020; Pierson, 2000). Taken together, these factors have the potential to create resistance in higher education towards change, and current and past practices could constrain options for the future (Schreyögg et al., 2011; Sydow et al., 2009). One current external demand for change in university practices is the digital transformation of society, which is pushing for universities to change their organisational models and tuition practices (Larsson & Teigland, 2019). This digitisation and the implementation of AI tools and services are suggested by some to be accelerating in the post-pandemic era, where new technologies both complement and challenge existing practices (Komljenovic, 2022). The next section briefly outlines what is meant by AI in the context of higher education practices.

1.2. Artificial intelligence in higher education

Drawing on various definitions of AI from current educational discourses (Bearman et al., 2022; Holmes et al., 2022; Luckin et al., 2022), AIED can be understood through the increasing variety of tools and systems deployed in higher education practices. In this respect, AIED can mean the vast family of AI tools that, although constituted by similar techniques and approaches, become different when used in teaching and learning activities with certain groups of students. This paper adopts Holmes et al.'s distinction between putting AI at the service of (1) the students (i.e., 'learning with AI'), (2) the teachers 'using AI to learn about student performance', and (3) the institutions 'learning about AI' and 'preparing for AI'. (Holmes et al., 2022; Holmes & Tuomi, 2022; Luckin et al., 2016). An example of AI applications being used in higher education is learning analytics systems, which enable teachers to analyse student data to predict student success and provide personalised feedback (Cerratto Pargman & McGrath, 2019). Other examples include AI-driven assessment tools (particularly those that utilise algorithmic decision-making systems) and so-called automatic short-answer grading systems, which are said to provide efficient, cost-effective solutions for the assessment of large classes (Burrows et al., 2015).

While using student data to design pedagogical interventions aligned with student needs seems promising, there are concerns regarding their impact on student learning and teachers' practices (Zawacki-Richter et al., 2019). Such concerns relate, for instance, to bias and discrimination (Mittelstadt et al., 2016) due to the nature of the data collected and the models employed, as well as the learning analytics applied to such data. This has led some to question whether *all* students should benefit from AIED-based pedagogical interventions, or only those marginalised by the education system (Cerratto Pargman et al., 2023).

Yet, discussions on AIED seem to assume that 'one size fits all' and overlook the great diversity of student groups attending university programmes. Moreover, there is a lack of consensus over whether AIED systems actually improve student learning or teacher practices (Zawacki-Richter et al., 2019). Consequently, despite high expectations, AIED is still in its infancy and the potential of the field remains largely unrealised (Luckin et al., 2016). As discourses about the potential of emerging technologies such as AIED increasingly gain attention, and students leave behind fine granular data of their interactions with university learning management systems (LMS), it is reasonable to ask whether universities have an obligation to act in specific ways towards particular students. This is the focus of the next section.

1.3. An obligation to act

Setting aside the empirical question of whether AIED tools and systems work, a range of ethical issues remain related to the opportunities arising in the digital age. As LMS such as Its Learning, Moodle, and Google Classroom become more commonly used, universities are accumulating vast amounts of data potentially capable of informing about student behaviour and predicting student performance. Using LMS-generated data (Stöhr et al., 2019) (e.g., timestamps of students' assignments submitted to analytics about the frequency of student interaction with the LMS's content) and algorithmic predictive models makes it easier for universities to identify students at risk of failure. At the same time, it raises questions about the ethical and moral implications of university teachers using such systems.

Accordingly, this study is partly inspired by Prinsloo and Slade, who argue that universities that have fine granular data about student performance have an obligation to act and that this obligation *"flows from both higher education's mandate to ensure effective and appropriate teaching and learning and its fiduciary duty to provide an ethical and enabling environment for students to achieve success"* (Prinsloo & Slade, 2017, p. 46). They also argue that technological advances, such as learning analytics and machine learning, may impact institutions' responsibilities towards their different stakeholders – particularly students (Prinsloo & Slade, 2017). Reich and Ito (2017) report that different groups of students benefit from digital technologies in different ways. As such, teachers committed to a more socially just university may be willing for certain groups of students to be targeted using emerging technologies. Although it can be argued that such responsibilities exist, a responsibility is not as strong as an obligation and, e.g., considerations of privacy may prohibit the use of certain AIED tools in certain circumstances. More persuasive is the growing tendency in modern ethics to talk about ethical reasons that give rise to obligations if weighty enough – reasons that may be based on considerations of equity, fairness, justice, need, benefit, harm-avoidance, autonomy, privacy, etc. (Parfit, 1984, 2011).

Box 1
The three case descriptions.

- Case A: A 25-year-old student who is studying at your department is having difficulties with their studies. **The student is the first in their family to attend higher education.** In addition to their studies, the student works 25 h a week.
- Case B: A 25-year-old student who is studying at your department is having difficulties with their studies. **Both the student's parents have higher education degrees.** In addition to their studies, the student works 25 h a week.
- Case C: A 25-year-old student who is studying at your department is having difficulties with their studies. **The student has a diagnosed learning disability.** In addition to their studies, the student works 25 h a week.

Bearing in mind higher education institutions' resistance to change and the significance of emerging AI technologies, there is a need to explore teachers' intuitions about the responsibility or ethical reasons to act. An online survey was designed to address the following research questions: RQ1) What are university teachers' intuitions around universities' responsibilities to adopt new AI technologies? RQ2) What are the conditions under which university teachers consider AIED defensible and, hence, would be willing to introduce such tools and services into their daily practice? RQ3) What are university teachers' self-reported knowledge of AI?

2. Method

An experimental philosophy approach was chosen (Knobe, 2006, 2007) for the study, as *"characteristically, experimental philosophers use empirical techniques to investigate philosophically significant intuitions about cases. An intuition, in this context, is a spontaneous judgement a person makes about a case with little or no conscious reason for their judgement"* (Mallon & Nichols, 2011). Accordingly, a cross-sectional survey study design was used. The completion of the survey was voluntary, and none of the information collected was personally identifiable.

2.1. The survey

In experimental philosophy, a common practice is to present information in the form of cases, change just one variable, and then examine the difference in the respondents' responses – potentially to that single change (Björk et al., 2015; Knobe, 2007; Mallon & Nichols, 2011). In order to examine whether equity is central to the teachers' perceptions of responsibility, three different student cases were created (see Box 1), which were identical in all aspects but one. The three cases represented three examples of a student that teachers are likely to encounter: a first-generation academic student (Case A), a student from an academically adept background (Case B), and a student with a learning disability (Case C). The cases were created to evoke different intuitions in the teachers on issues of responsibility and equity, which are important to examine in light of the study's purpose. First-generation students (Case A) in higher education were chosen because research shows that they encounter a wide range of academic and social challenges, have lower grades, and higher attrition rates (Aruguete, 2017; Beattie, 2018; Ives & Castillo-Montoya, 2020). Students from academically adept backgrounds (Case B) represent the archetypical university student. The third category represents students with learning disabilities (Case C), who are protected by Swedish law and universities have a legal responsibility to assist them. However, these students' level of need may often not be known to university teachers, who may also be unaware of their legal obligations. Students with learning disabilities must also self-identify as such and present documentation to support their case in order to receive assistance. Research suggests students in need of assistance have difficulty providing this documentation and run the risk of not getting the support they need (Harrison et al., 2008). It is obviously possible that some students could be found in cases A and C simultaneously, as well as in cases B and C simultaneously.

One of the scenarios in Box 1 was presented to the respondents (in each of the surveys) together with the same description of the potential benefits of AI, as well as a text explaining that AI practices are expensive and may require working with a learning analytics analyst. Also attached was the United Nations International Children's Emergency Fund's (UNICEF) definition of AI: *"AI refers to machine-based systems that can, given a set of human-defined objectives, make predictions, recommendations, or decisions that influence real or virtual environments. AI systems interact with us and act on our environment, either directly or indirectly. Often, they appear to operate autonomously, and can adapt their behaviour by learning about the context"* (UNICEF, 2021, p. 16).

An electronic, web-based, anonymous survey (see appendices for the full survey) was used, consisting of case descriptions followed by 18 questions (in this paper, the term 'question' is used to denote both the statements and questions used in the survey). Survey questions 2, 3, 4, 6 and the free text responses addressed RQ1, questions 5 and 7 and the free text responses addressed RQ2, and question 1 and the free text responses addressed RQ3. The survey is, to our knowledge, the first of its kind to examine equity using an experimental philosophy approach, so when designing it, careful attention was given to creating coherence between questions and response alternatives. As part of the validation process, the questionnaire was put through pilot testing and cognitive interviews (Collins, 2003; Wolcott & Lobczowski, 2021). The survey was piloted with a group of nine university teachers and education researchers, and two survey experts. The group provided feedback about the feasibility and usability of the survey, the clarity of the questions, and whether the response options aligned well with the questions. The feedback was used to modify some of the questions and then the survey was retested with one survey expert. During the cognitive interviews, the authors sat with the pilot test group while they read the study information and filled in the survey, employing a 'think-aloud' methodology (Wolcott & Lobczowski, 2021). The participants then expressed their concerns or questions, and the survey was altered accordingly. All these steps were taken in order to enhance the face and content validity of the survey. Four kinds of response options were used: multiple choice, dichotomous, 4-point Likert responses, and free text answers. The questions pertained to their level of knowledge about AI, whether they believed the university had a responsibility to assist students in the case they had been given, students' responsibility for their studies, their responsibility to use AI to facilitate students' learning, and questions about their age, gender, experience and academic discipline (for further details see the appendices).

2.2. Participants and data collection

A non-probability convenience sample of university teachers (excluding Ph.D. candidates who had teaching duties) at one of the largest universities in Sweden was used to select participants. Their email addresses were acquired through the personnel department at the university. A total of 1,773 respondents were added to the survey from a range of teaching positions, e.g., adjunct lecturers, lecturers with an associate professor role, and lecturers with a full professor position. Some also had semi-administrative roles such as director of studies and

vice/head of department.

One of the three versions of the questionnaire was emailed to each participant via a survey tool (Survey and Report), plus three reminders to complete them. An introductory letter was attached, containing information about the project and informed consent. The respondents had to give their informed consent online to begin the survey. The letter did not mention the other two versions of the student cases, so the experimental aspect of the study was unknown to the respondents. The participants were randomly divided by faculty (science, social science, law, humanities) into three cohorts. A third of each faculty was then assigned to one of the three cases, which meant there was equal faculty distribution for each case.

2.3. Data analysis

The completed surveys were exported to SPSS version 28.0.1.1 (IBM Corporation, Armonk, NY) for descriptive and inferential statistical analysis. The data distribution was assessed visually via boxplots and by looking for discrepancies among the parameters of central tendency, evaluating the skewness of the distributions, and employing Shapiro-Wilk tests. Some variables were dichotomised or trichotomised into categorical variables to facilitate further exploration, or due to insufficient data points. The outcome variables were the perceptions of institutional and individual responsibility for using AIED practices, as measured by item scores on the questionnaire. The background variables were gender, age, faculty, academic position, years as a university teacher, and regular teaching time.

For the analysis of categorical variables, frequencies and percentages were calculated; for scale variables, mean and standard deviations (SD or symbolised as ±) were used. As many of the variables were on an ordinal scale level, and the data showed evidence of skewness in normal distribution and deviation in homogeneous variance (thus violating assumptions for the choice of parametric procedures), the data were analysed using a non-parametric approach. Since that approach is based on comparing differences in the median value rather than the mean value, the median and interquartile ranges (IQR) were calculated as location and dispersion measures. However, as it can sometimes be challenging to recognise differences in median values, mean values and SD were also calculated to clarify any differences between groups. Consequently, non-parametric statistical tests were performed to avoid influences of the distribution of the data.

The Mann-Whitney *U* test was used for the independent ordinal data, while the Kruskal-Wallis (one-way analysis of variance) test was used for independent between-group analyses. P-values were adjusted for multiple comparisons using the Bonferroni correction. As an effect size measure, rank-biserial correlation (r_B) was used for the Mann-Whitney *U* test, employing threshold values of <0.1 = trivial, 0.1 = small effect, 0.3 = medium effect, and 0.5 = large effect (Goss-Sampson, 2019). For the Kruskal-Wallis test, eta squared based on the H-statistic (η^2) was applied to assess the effect size, using interpretation values of <0.01 = trivial, 0.01 = small effect, 0.06 = moderate effect, and 0.14 = large effect (Goss-Sampson, 2019). As SPSS cannot calculate effect size for the Kruskal-Wallis test, it was done manually using the formula (H – k + 1)/(n – k), where 'H' is the value obtained in the Kruskal-Wallis test, 'k' is the number of groups, and 'n' is the total number of observations (Tomczak & Tomczak, 2014).

To investigate categorical nominal-scale variables, one 2x6 and two 3x6 contingency tables were created. Chi-square ($\chi 2$) test of independence was used to assess associations between the nominal-scale variables. To see which frequencies differed, standardised adjusted residuals were calculated for the observed frequencies and expected frequencies. Residuals of greater or less than ±1.96 were used as the cut-off for a significance level of $p < 0.05$. For the Chi-square test, Cramer's V was used as a measure of effect size, considering values as 0.1 = small effect, 0.3 = medium effect, and 0.5 = large effect (Goss-Sampson, 2019). The data fulfilled the assumptions of the Chi-square test of independence. Thus, both variables were categorical, all observations were independent, and the cells in the contingency tables were mutually exclusive. If the expected value of cells was ≤5 and the Chi-square test assumption was violated, the Fisher's Exact test was employed. Probability values less than 0.05 were considered statistically significant for statistical tests.

The qualitative data extracted from the open questions with free-text answers were analysed thematically to exemplify the range of issues that was identified. A form of constant comparative analysis was adopted, where the data were coded, compared, sorted and described as themes, which were revised until a coherent whole was formed (Sandelowski & Barroso, 2002). Before the final description of the synthesised themes, all the authors discussed the content of the themes until a consensus was reached on their credibility.

3. Results

The results from the quantitative part of the study are presented in detail below, together with a brief summary of the free-text responses.

3.1. Quantitative results

A total of 194 teachers responded. For Case A, 8.7% of the teachers completed the questionnaire. For cases B and C, the response rates were 10.5% and 12.6%, respectively. The respondents included 99 females (51%) and 89 males (49%), and six participants identified as non-binary gender or did not disclose. The mean age of the sample was 52.1 (SD 8.4), with ages ranging between 35 and 80. Tables 1–3 present the results for questions 1, 2, 3, 4, and 6 for each of the cases. The results for Q5 are presented in Table 4 and the results for Q7 are presented as text. This is followed by the demographic data in Table 5. The tables specify which survey questions are predominantly related to the research questions.

Question 7's wording was: *"Would you be willing to allocate some of*

Table 1
Percentages of Likert responses, means and standard deviations (SD), and median and interquartile ranges (IQR) for Case A (first-generation student).

	Strongly disagree %	Disagree %	Agree %	Strongly agree %	Mean (SD)	Median (IQR)
I have knowledge about Artificial Intelligence. [a] (*n* = 57)	10.5	26.3	49.1	14.0	1.7 (0.8)	2.0 (1.0)
Universities should use new technologies to address individual students' learning needs.[b] (*n* = 57)	1.8	17.5	68.4	12.3	1.9 (0.6)	2.0 (0)
Universities have a responsibility to provide education on an equitable basis.[b] (*n* = 57)	1.8	19.3	59.6	19.3	2.0 (0.7)	2.0 (0)
The above student is responsible for completing her studies.[b] (*n* = 57)	1.8	5.3	57.9	35.1	2.3 (0.6)	2.0 (1.0)
University teachers have a responsibility to allocate teaching time to work with a learning analyst or AI/LA tools to facilitate the above student's learning. (*n* = 57)	29.8	47.4	22.8	–	0.9 (0.7)	1.0 (1.0)

[a] Question measures constructs related to RQ3 (What are teachers' self-reported knowledge of AI?).
[b] Question measures constructs related to RQ1 (What are university teachers' intuitions around universities' responsibilities to adopt new AI technologies?).

Table 2
Percentages of Likert responses, means and standard deviations (SD), and median and interquartile ranges (IQR) for Case B (archetypical student).

	Strongly disagree %	Disagree %	Agree %	Strongly agree %	Mean (SD)	Median (IQR)
I have knowledge about Artificial Intelligence.[a] ($n = 62$)	8.1	32.3	48.4	11.3	1.6 (0.8)	2.0 (1.0)
Universities should use new technologies to address individual students' learning needs. [b] ($n = 61$)	3.3	16.4	72.1	8.2	1.8 (0.6)	2.0 (0)
Universities have a responsibility to provide education on an equitable basis.[b] ($n = 61$)	3.2	14.5	71.0	11.3	1.9 (0.7)	2.0 (0)
The above student is responsible for completing her studies.[b] ($n = 62$)	1.6	3.2	56.5	38.7	2.3 (0.6)	2.0 (1.0)
University teachers have a responsibility to allocate teaching time to work with a learning analyst or AI/LA tools to facilitate the above student's learning. [b] ($n = 61$)	23.0	63.9	13.1	–	0.9 (0.6)	1.0 (0)

[a] Question measures constructs related to RQ3 (What are teachers' self-reported knowledge of AI?).
[b] Question measures constructs related to RQ1 (What are university teachers' intuitions around universities' responsibilities to adopt new AI technologies?).

Table 3
Percentages of Likert responses, means and standard deviations (SD), and median and interquartile range (IQR) for Case C (student with a learning disability).

	Strongly disagree %	Disagree %	Agree %	Strongly agree %	Mean (SD)	Median (IQR)
I have knowledge about Artificial Intelligence. [a] ($n = 75$)	9.3	32.0	52.0	6.7	1.6 (0.8)	2.0 (1.0)
Universities should use new technologies to address individual students' learning needs. [b] ($n = 73$)	2.7	15.1	65.8	16.4	2.0 (.7)	2.0 (0)
Universities have a responsibility to provide education on an equitable basis.[b] ($n = 74$)	4.1	6.8	50.0	39.2	2.2 (0.8)	2.0 (1.0)
The above student is responsible for completing her studies. [b] ($n = 74$)	1.4	6.8	54.1	37.8	2.3 (0.7)	2.0 (1.0)
University teachers have a responsibility to allocate teaching time to work with a learning analyst or AI/LA tools to facilitate the above student's learning. [b] ($n = 73$)	16.4	57.5	23.3	2.7	1.1 (0.7)	1.0 (1.0)

[a] Question measures constructs related to RQ3 (What are teachers' self-reported knowledge of AI?).
[b] Question measures constructs related to RQ1 (What are university teachers' intuitions around universities' responsibilities to adopt new AI technologies?).

Table 4
Responses to Q5: If a student such as the one described above were offered individual help to complete her studies, would it affect your confidence in the university?[a].

	My confidence would increase	My confidence would not be affected	My confidence would decrease
Case A	29.1	65.5	5.5
Case B	14.5	69.4	16.1
Case C	44.6	50.0	5.4

[a] Question measures constructs related to RQ2 (What are the conditions under which university teachers consider AIED defensible and, hence, would be willing to introduce such tools and services into their daily practice?).

your teaching time to work with a learning analyst or AI/LA tools to facilitate the above student's learning?" It predominantly addressed RQ2. There, 58.9%, 48.4%, and 65.3% in cases A, B, and C respectively, reported being willing to allocate some teaching time to work with a learning analyst or AI/LA tools to facilitate students' learning.

3.1.1. Demographic distinctions case A: first-generation student

There were no statistical differences or associations between the background variables and questions.

3.1.2. Demographic distinctions case B: archetypical student

The data for this case showed statistically significant differences ($p = 0.004$, $r_B = 0.402$) regarding knowledge about AI between women (1.6 ± 0.9; mdn 2.0, IQR 1.0) and men (1.8 ± 0.9; mdn 2.0, IQR 1.0). Statistically significant differences regarding AI knowledge were also detected according to academic position ($p = 0.027$; $r_B = 0.314$), where lecturers and senior lecturers scored lower (1.5 ± 0.8; mdn 1.5, IQR 1.0) than professors (2.0 ± 0.6; mdn 2.0, IQR 0). There were also statistical differences regarding AI knowledge according to the number of years engaged as a university teacher ($p = 0.043$; $\eta^2 = 0.074$). Ensuing this with pairwise comparisons disclosed that teachers with more than 30 years of experience scored (2.2 ± 0.5; mdn 2.0, IQR 0.5) significantly higher ($p = 0.047$) than teachers with less than ten years of experience (1.3 ± 0.6; mdn 1.0, IQR 1.0).

With regard to responsibility for allocating teaching time to work with a learning analyst or AI/LA tools, professors scored statistically significantly ($p = 0.019$; $r_B = 0.307$) higher (1.1 ± 0.5; mdn 1.0, IQR 0) than lecturers and senior lectures (0.8 ± 0.6; mdn 1.0, IQR 1.0).

There was a statistically significant association between years spent as a university teacher and willingness to allocate teaching time to work with a learning analyst or AI/LA tools ($p = 0.031$, Cramer's $V = 0.320$). A post hoc analysis revealed that the teachers who had worked 11–30 years were significantly less willing to allocate time than expected, while teachers who had worked >31 years were significantly more willing to allocate time than expected.

3.1.3. Demographic distinctions case C: student with a learning disability

There was a highly statistically significant gender difference ($p < 0.001$; $r_B = 0.417$) regarding knowledge about AI between women (1.3 ± 0.7; mdn 1.0, IQR 1.0) and men (1.9 ± 0.7; mdn 2.0, IQR 0). Likewise on the question of whether universities had a responsibility to provide education on an equitable basis ($p < 0.024$; $r_B = 0.280$), with women scoring higher (2.4 ± 0.7; mdn 2.0, IQR 1.0) than men (2.0 ± 0.6; mdn 2.0, IQR 1.0). Statistically significant gender differences ($p = 0.009$, $r_B = 0.316$) were also revealed regarding students' responsibility for Det star ju efter! 1.3 vs 1.9 completing their studies, with more men agreeing with the statement (2.5 ± 0.6; mdn 3, IQR 1) than women (2.1 ± 0.6; mdn 2.0, IQR 0). There was a statistically significant association between gender and the respondents' confidence in the university if students were offered support to complete their studies ($p = 0.031$,

Table 5
Demographic data for the cohort across all three cases.

Demographic variable	Level of variable	Case A n = 57	Case B n = 62	Case C n = 75	All cases n = 194
Gender[a]	Female (%)	31 (54.4)	31 (50.0)	37 (49.3)	99 (51.0)
	Male (%)	24 (42.1)	29 (46.8)	36 (48.0)	89 (45.9)
	Other	–	1 (1.6)	–	1 (0.5)
	Don't want to answer	2 (3.5)	1 (1.6)	2 (2.7)	5 (2.6)
Age (years)	Mean (SD)	52.1 (7.8)	52.0 (8.5)	52.0 (7.8)	52.1 (8.0)
	Min-Max range	34–70	35–80	35–68	34–80
Faculty	Humanities	16 (28.6)	21 (34.4)	20 (27.0)	57 (29.8)
	Law	3 (5.4)	1 (1.6)	5 (6.8)	9 (4.7)
	Science	6 (10.7)	8 (13.1)	12 (16.2)	26 (13.6)
	Social Science	31 (55.4)	31 (50.8)	36 (48.6)	98 (51.3)
	Other	–	–	1 (1.4)	1 (0.5)
Academic position	Adjunct lecturer	1 (1.8)	2 (3.2)	5 (6.8)	8 (4.2)
	Lecturer	32 (57.1)	34 (54.8)	47 (63.5)	113 (58.9)
	Professor	21 (37.5)	23 (37.1)	21 (28.4)	65 (33.9)
	Other	2 (3.6)	3 (4.8)	1 (1.4)	6 (3.1)
Years as a university teacher	Mean (SD)	17.1 (9.1)	18.2 (9.5)	18.2 (8.2)	17.9 (8.9)
	Min-Max range	2–35	1–50	1–38	1–50
Teaching time (0–100%)	Mean (SD)	38.5 (21.5)	43.6 (24.6)	48.8 (24.7)	44.1 (24.0)
	Min-Max range	0–80	0–100	0–100	0–100

[a] Analysis of gender was only conducted for female and male due to insufficient data for other categories.

Cramer's V = 0.293). Post hoc analysis revealed that more female teachers than expected reported that their confidence would increase, while fewer men than expected stated that their confidence would increase.

The data also revealed statistical differences among trichotomised age groups regarding teachers' responsibility to allocate time to work with a learning analyst or AI/LA tools ($p = 0.020$; $\eta^2 = 0.083$). Teachers aged over 64 years agreed more (2.0 ± 0.9; mdn 2.0, IQR 2.0) than teachers aged 46–63 (1.0 ± 0.6; mdn 1.0, IQR 0) and those aged 45 and younger (1.2 ± 0.7; mdn 1.0, IQR 1.0). A post hoc analysis showed a statistically significant difference ($p = 0.018$) between teachers aged over 64 and those aged 46–63. Another statistically significant association was between age groups and teachers' responsibility to allocate teaching time to work with AI/LA to facilitate learning ($p = 0.024$, Cramer's V = 0.330). A post hoc analysis using adjusted residuals showed fewer teachers aged 46–63 were willing to do so than expected.

The analysis also revealed statistically significant differences ($p = 0.009$, $r_B = ?$) between teachers from different faculties regarding students' responsibility for completing their studies. Pairwise comparisons showed teachers from the humanities faculty (2.1 ± 0.7; mdn 2.0, IQR 1.0) agreed significantly less with the statement than teachers from the natural sciences (2.4 ± 0.5; mdn 2.0, IQR 1.0) and teachers from the social sciences (2.4 ± 0.7; mdn 2.0, IQR 1.0) ($p = 0.013$ and $p = 0.015$, respectively).

3.2. Findings from free-text responses

There was a total of 80 free text responses, with 18 coming from respondents to Case A, 27 from Case B, and 35 from Case C. The responses were generally only one sentence long, so did not permit an in-depth analysis, but they addressed all three of the research questions and could be categorised into three themes: 1) Fear/Scepticism, 2) Knowledge, Resources and Structure, and 3) Fairness and Responsibility. A quote illustrates each theme below. The respondents did not know about the other cases, which suggests other issues around equity could have been revealed had the respondents been aware of the different cases or had been asked to prioritise them.

3.2.1. Fear and scepticism

The responses in this theme included statements relating to fears that AI would replace teachers and have a negative impact on teaching practices. Some had concerns about how AI technologies could be used by repressive regimes, including outside of the teaching context. Some thought that AI tools were still too early in their development and too imprecise to be used in teaching and learning contexts. Others were sceptical over the hype and overconfidence in AI, while some believed that the effectiveness of AI depended a lot on the field of teaching, with one respondent writing:

> *"The possible applicability of AI varies greatly depending on the subject area. In my subject of humanities, it seems completely inapplicable."* (Respondent, Case B)

By chance, the survey closed approximately one week before the news of OpenAI and ChatGPT became widespread.

3.2.2. Knowledge, Resources and Structure

This theme was characterised by reports of having too little knowledge about AI in general, but also with respect to the specifics of AI in the context of teaching and learning. There was an emphasis on assessment and subject delivery, but also AI was identified as a way of identifying and preventing plagiarism. Here, AI was seen both as a threat and an opportunity.

Respondents reported lacking both knowledge and resources to engage with and learn about AI. The most common resource mentioned was in the form of time to dedicate to learning new tools. This was mostly brought about by having a very heavy workload.

> *"I would spend time on AI as a learning tool if the university had the resources to provide our department with an IT and computer assistant, and if I was provided with enough time to learn about teaching with AI."* (Respondent, Case A)

Structural issues related to questions of responsibility were also mentioned. Here, the respondents expressed that universities had a structural ownership of matters of teaching and learning, e.g., through allocating teaching time and deciding what that time should include. They also thought that universities would need to strategize to bring about such AI interventions.

3.2.3. Fairness and responsibility

A recurring sentiment was that university students were responsible for completing their studies – irrespective of their personal situation and needs. Fairness and responsibility were also raised by the respondents, who reasoned that giving extra help to one student would come at a cost to other students. The teachers also commented that no student should get any extra benefit or access to a teacher outside of what the other students were offered. Others were aware that students with learning disabilities were guaranteed extra assistance, and that this assistance was provided by student services, i.e., outside their teaching duties or

responsibility.

> *"Just noting that the teaching I do is meant to help students to learn and pass the courses, and I do pay attention to students' individual questions and needs – at least to some extent. But, for me, it is of key importance that students also take responsibility."* (Respondent, Case B)

4. Discussion

This study focused on university teachers' intuitions regarding universities' responsibility to act on the opportunities and challenges that AI brings to higher education. In doing so the study targets three overriding questions: What are university teachers' intuitions around universities' responsibilities to adopt new AI technologies? What are the conditions under which university teachers consider AIED defensible and, hence, would be willing to introduce such tools and services into their daily practice? And what are university teachers' self-reported knowledge of AI?

4.1. University teachers' intuitions around universities' responsibilities to adopt new AI technologies

Across all three cases, a majority of respondents indicated that universities had a responsibility to provide students with AI tools and services, reasoning that AIED tools should be used for more equitable outcomes. However, in Case A (first-generation student) and Case C (student with a learning disability), the respondents indicated that universities should use AIED tools and systems to a higher degree to achieve equitable outcomes. This suggests that the respondents in this study generally supported Prinsloo and Slade's assertion that universities have an obligation to act on considerations of equity and fairness (Prinsloo & Slade, 2017). Moreover, there was a statistically significant gender difference, with women scoring higher than men on the statement that AIED tools should be used to achieve equitable outcomes. So, while women self-report having less knowledge about AI than men, they argue to a higher degree than men that AIED tools should be used to bring about equitable outcomes. On the question of whether the respondents' confidence in the university would change if the student in the case received assistance from AI, a significant difference was found between Case C, where the respondents' confidence would increase, and Case B, where the respondents' confidence would decrease. This suggests that the respondents believed that students from vulnerable groups, particularly those with a learning disability, should benefit from AI assistance and that there were equity-based reasons to do so. It may therefore be interesting to explore whether people of different genders approach the question of equity in different ways. Are some groups more likely to align with an ethics of care approach to normative reasoning (Tronto, 1998) that claims moral action centres on interpersonal relationships, while others align with more impartial approaches to issues of ethics and equity? There is a potentially interesting tension here, if university teachers have strong intuitions about how resources are dedicated and which students should receive help, but resources are distributed following an institutional logic. The results of this study align with previous studies on the differences between university teachers' perceptions of institutional and personal responsibility (Cerratto Pargman & McGrath, 2021).

4.2. On the conditions under which university teachers in Sweden consider AIED defensible

Empirical studies on equity remain underrepresented in higher education research, particularly in relation to the emergence of new technologies, though related work identifies how new technologies could be used to help students and identify those at risk of failing (Cheddadi & Bouache, 2021). Few studies target equity as a research object, and in the Swedish context this seems to be the first study addressing equity in higher education – certainly in relation to how AI tools are used. Accordingly, more research is needed to determine what role equity plays in university teachers' reasoning about the uptake of technology. At the same time, the free text responses suggested that the respondents were wary of the cost of providing additional help to specific students, and had concerns that such help may come at a cost to other students. The free text responses also identified other concerns about fairness and responsibility. The respondents felt that institutions had a responsibility to ensure that such measures were taken, but that such work could not be included within the scope of their current duties. The experimental philosophical approach in this study did not reveal the existence of the other types of student scenarios. While university teachers are aware of such students, this study can be used in discussions about how AI technology is developed and deployed in higher education, and how prioritisations are made.

While the respondents thought universities should use AIED tools and systems to facilitate student learning, they also thought university teachers did not have a responsibility to allocate teaching time to work with a learning analyst. This seems to be a statement of personal moral responsibility. In the free text responses, some teachers expressed a desire to have the requisite AI literacy to engage with AI tools and systems. At the same time, the respondents felt that teachers had a greater responsibility towards first-generation students, and students with learning disabilities. Interestingly, 58.9%, 48.4%, and 65.3% in cases A, B and C, respectively, reported being willing to allocate teaching time to work with a learning analyst to facilitate student learning. This raises further questions as to how such students can be identified in a context where this information is not generally available to teachers. Could, for example, analytics dashboards be used for students to self-identify as a first-generation student, or as having a learning disability? If so, how might such additional help be directed to such students? That said, individual teachers may not be ready to offer such directed support (Luckin et al., 2022; Laupichler et al., 2022). While the findings of this study align with previous work (Liu et al., 2020), they offer new insights into university teachers' reasoning about how resources should be distributed.

4.3. On university teachers' self-reported knowledge of AI

Statistical differences relating to gender were found regarding teachers' knowledge about AI, with medium to large effect sizes across two of the three cases (B and C), where men reported a higher degree of knowledge than women. In this study, the respondents were not asked about the depth or accuracy of their self-reported AI knowledge. In Case B, there was a significant difference across academic positions, where professors were more likely to self-report higher knowledge of AI. However, some respondents may have been more confident than others about their knowledge of AI or had an inaccurate understanding of what AI actually entails. A follow-up study is underway on university teachers' factual knowledge of AI systems and tools. That women reported having less knowledge of AI than men is interesting, and similar findings have been reported elsewhere (Rainey et al., 2021). This study does not explain why this is so, but given the complex and imprecise conceptualisations surrounding AI (Bearman et al., 2022; Laupichler et al., 2022), more work is needed to understand this. Such work should use surveys to determine differences by gender and position about university teachers' understanding of AI, as well as examine qualitatively how university teachers reason about AI.

More troubling is the many respondents who reported having little or no knowledge about AI across the three cases (Case A, 36.8%; Case B, 40.4%; Case C, 41.3%), and similar findings have been reported elsewhere (Liu et al., 2020). Knowledge about AI is central to the willingness and ability to implement it in teaching and learning practices, so it is unlikely that these university teachers could currently do that. Consequently, universities must enhance teachers' AI literacy so students can use it to learn, teachers can use it to learn about student performance,

and institutions can prepare for the future (Holmes et al., 2022; Luckin et al., 2022). However, institutions must allocate adequate time and resources for this to happen.

Considering the results of this study in light of the concept of path dependency, a central characteristic of organisations like universities is that they develop through homeostatic feedback processes whose function is to regulate outside threats and maintain equilibrium (Schreyögg et al., 2011). Emerging AIED technologies represent one such threat, especially when teachers report inadequate knowledge to implement them. These concerns align with previous research on path dependency and the institutionalisation of technology (Krücken, 2003), and the implementation of data-driven practices and innovation in higher education (McGrath & Åkerfeldt, 2019). The fact that more support is needed to help teachers develop AI competency and literacy is established across several research fields (Chounta et al., 2022; Laupichler et al., 2022; Rainey et al., 2021). It seems that that targeting university teachers' AI literacy and readiness (Luckin et al., 2022) may be a key component in overcoming resistance to change and offsetting destructive forms of path dependency where current practices are insulated against change.

5. Conclusion and future directions

This survey is, to the authors' knowledge, the first to take an experimental philosophical approach to university teachers' intuitions on the uptake of AI technology, and it therefore is a valuable contribution to the research literature. A large number of the university teachers self-reported low levels of understanding about AI, but a substantial percentage of them also thought AI could contribute to a more equitable system of support for students. From a competency development perspective, university teachers may need training to understand the implications of AI technologies for their teaching, and to better prepare them for the other technologies currently being deployed across higher education.

6. Limitations and future work

The survey was sent to all the teachers at one of Sweden's largest universities. We acknowledge that some of the respondents approached may not have had active teaching positions either through administrative duties, or by virtue of the fact that they are currently on research sabbaticals, or international visits and exchanges, or due to extensive research activities but we decided to send to all potential respondents who fulfilled the criteria.

The response rate across the three cases was low (Case A, 8.7%; Case B, 10.5%; Case C, 12.6%), so care must be taken when attempting to generalise from the findings. Also, the data on the respondents' level of knowledge of AI systems and tools is merely self-reported and estimated, so caution should be taken when interpreting these results. Finally, while a thematic overview of the free text responses is given in this paper, it is important to understand that further studies are needed to unpack these questions in more depth. More qualitative studies examining technology uptake from an equity perspective are therefore needed, but so is work targeting different rationales and logics when implementing AI in higher education. Work examining ethical concerns related to teachers' ability to cope with AIED technologies also remains to be done.

Statements on open data and ethics

The data that support the findings of this study are not available. The survey is available as an appendix. Ethical approval for this study was granted by the Swedish Ethical Review Board (Dnr 2022-0105-01). The completion of the survey was undertaken on a voluntary basis, and none of the information collected was personally identifiable – thereby maintaining data anonymity. All the data were handled and stored in accordance with the Declaration of Helsinki.

Declaration of competing interest

The authors declare that they have no competing financial interests or personal relationships that could have influenced the findings reported in this study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.caeai.2023.100139.

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