Exploring Higher Education Students' Experience with AI-powered Educational Tools: The Case of an Early Warning System

Esplorare l'esperienza degli studenti universitari con strumenti educativi basati sull'IA: Il caso di un sistema di allerta precoce

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DOUBLE BLIND PEER REVIEW

ABSTRACT

AI-powered educational tools (AIEd) include early warning systems (EWS) to identify at-risk undergraduates, offering personalized assistance. Revealing students' subjective experiences with EWS could contribute to a deeper understanding of what it means to engage with AI in areas of human life, like teaching and learning. Our investigation hence explored students' subjective experiences with EWS, characterizing them according to students' profiles, self-efficacy, prior experience, and perspective on data ethics. The results show that students, largely senior workers with strong academic self-efficacy, had limited experience with this method and minimal expectations. But, using the EWS inspired meaningful reflections. Nonetheless, a comparison between the Computer Science and Economics disciplines demonstrated stronger trust and expectation regarding the system and AI for the former. The study emphasized the importance of helping students' additional experiences and comprehension while embracing AI systems in education to ensure the quality, relevance, and fairness of their educational experience overall.

Gli strumenti educativi alimentati dall'intelligenza artificiale (AIEd) includono sistemi di allerta precoce (EWS) per identificare gli studenti universitari a rischio, offrendo assistenza personalizzata. Rivelare le esperienze soggettive degli studenti con gli EWS potrebbe contribuire a una comprensione più profonda di cosa significhi interagire con l'IA in aree della vita umana quali l'insegnamento e l'apprendimento. La nostra indagine ha quindi esplorato le esperienze soggettive degli studenti con gli EWS, caratterizzandole secondo i profili degli studenti, l'autoefficacia, l'esperienza pregressa e la prospettiva sull'etica dei dati. I risultati mostrano che gli studenti, per lo più lavoratori senior con forte autoefficacia accademica, avevano esperienze limitate con questo metodo e aspettative minime. Ciononostante, l'utilizzo degli EWS ha ispirato riflessioni significative. Nonostante ciò, un confronto tra le discipline di Informatica ed Economia ha dimostrato una maggiore fiducia e aspettativa riguardo al sistema e all'IA per la prima. Lo studio ha sottolineato l'importanza di aiutare gli studenti a maturare ulteriori esperienze e comprensioni mentre si avvalgono dei sistemi AI nell'educazione per garantire la qualità, la rilevanza e l'equità della loro esperienza educativa complessiva.

KEYWORDS
Students' Experiences, Artificial Intelligence, Early Warning System, Higher Education, Thematic Analysis
Esperienze degli studenti, Intelligenza Artificiale, Sistema di Allerta Precoce, Alta formazione, Analisi tematica

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1. Introduction

Artificial Intelligence (AI) is increasingly transforming various industries and services (Makridakis, 2017), including education. AI is a tool that allegedly has the potential to address some of the biggest challenges in education today, promoting innovative teaching and learning practices, and accelerating progress (Popenici & Kerr, 2017; Zawacki-Richter et al., 2019). Though AI systems have been studied in education in the last 30 years, the general audience's attention has been particularly captured by what was called "Generative AI" (GenAI). Since November 2022, emerging technologies such as ChatGPT, created by the research company OpenAI (OpenAI, 2022), and Bard, developed by Google (Pichai, 2023) were launched and followed by thousands of applications after a year. Both are trained on "large language models", i.e., to predict the probability of various words in a given text to appear together, these tools are AI-based natural language processing and facilitate human-like conversations with chatbots, providing an exciting user experience (Jalalov, 2023; Lund & Wang, 2023).

A recent study by Tlili et al. (2023) focused on ChatGPT highlighted the necessity for AI-based teaching philosophy in Higher Education (HE), emphasizing the importance of enhancing AI literacy skills in the context of training for 21st-century capabilities (Ng et al., 2023). In such a context, it is relevant for the students to understand that several AI-driven tools might concur to shape their user experience in different ways. Indeed, several Educational AI (EdAI) tools before GenAI, particularly based on local developments by SMEs, might enhance students' experience and learning outcomes by automating both routine administrative tasks and promoting judgments based on data (Pedró et al., 2019). From the students' perspective, EdAI could support their independent learning, self-efficacy, self-regulation, and awareness of their progress (Jivet et al., 2020). Nonetheless, the lack of understanding of how AI-based tools work, and which are the digital infrastructures supporting their existence might create unrealistic expectations or unawareness about unauthorised data capturing with its consequent manipulation. A key approach to AI literacy is based indeed on transparency and the users' agency to decide at which point the system should be stopped for it is not serving educational and overall human purposes while working (Floridi, 2023)

In connection with the perspective above, several works (Pedró et al., 2019; Rienties et al., 2018; Scherer & Teo, 2019; Valle et al., 2021) point out that evaluating users' perceptions and opinions about EdAI tools is crucial. A study by Raffaghelli et al. (2022) investigated factors connected to students' acceptance (a form of opinion) of an AI-driven system based on a predictive model capable of early detection of students at risk of failing or dropping out, or EWS (Bañeres et al., 2020; Bañeres et al., 2021; Raffaghelli, Rodríguez, et al., 2022). The study investigated how acceptance changed over time (Greenland & Moore, 2022). Following a pre-usage and post-usage experimental design based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003), authors explored the factors influencing EWS acceptance included perceived usefulness, expected effort, and facilitating conditions. Social influence was the least relevant factor. Interestingly, our findings also revealed a disconfirmation effect (Bhattacherjee & Premkumar, 2004) in accepting the AI-driven system: a difference between expectations about using such a technology and the post-usage experience. Despite high satisfaction levels after using the system, Raffaghelli, Rodríguez, et al. (2022) suggested that even though AI is a trendy topic in education, careful analysis of expectations in authentic settings is needed. However, the study's quantitative nature could not fully understand students' expectations, beliefs, motivations, and experiences with a specific AI-driven system.

The current study investigates students' acceptance of an AI-driven system (EWS) based on thematic discourse and content analysis. Such models can warn students and teachers about at-risk situations through dashboards or panel visualisations based on local data generated by the LMS adopted by the university (Liz-Domínguez et al., 2019). Most importantly, an EWS may also provide intervention mechanisms, helping teachers provide early personalised guidance and follow-up with the students to amend possible issues. combined with their knowledge impacts their acceptance of such developments in HE. The effectiveness of an EWS lies not only in its technical performance but also in students' and teachers' experiences, opinions, and perception of usefulness and relevance for their learning and teaching practices. This aligns with the debate on AI literacy for understanding the EWS operation and technological infrastructure might lead the students to act agentically relating to an AI-driven technology.

2. Background

The cross-disciplinary research field on EdAI tools has multiple perspectives: social scientists focus on human aspects, potential benefits, and ethical concerns, (Prinsloo, 2019; Selwyn, 2019; Tzimas & Demetriadis, 2021) and, in contrast, STEM researchers focus on technical aspects like usability and user experience (UX) issues (Bodily & Verbert, 2017; Hu et al., 2014; Rienties et al., 2018). Qualitative studies on stakeholders' experiences are scarce and recent, and there is a need for better understanding (Ghotbi et al., 2022; Kim et al., 2019; Zawacki-Richter et al., 2019). Below, we reviewed the literature about general experiences relating to AI in education, then experiences in EWS as a particular case, primarily focused on the student's perspective.

Much of the literature agrees that perceived usefulness and ease of use are positively related to EdAI tool usage intention, both in teachers (Chocarro et al., 2021; Rienties et al., 2018) and in students (Chen et al., 2021; Chikobava & Romeike, 2021; Kim et al., 2020). Gado et al., (2022) found that perceived knowledge of AI, especially in female students, is crucial for effective AI training approaches in various disciplines. Many students considered AI a diffuse technology, suggesting the need to design AI training approaches in the psychology curricula. This need has also been emphasised in other disciplines, such as medicine (Bisdas et al., 2021), business (Xu & Babaian, 2021), and even computer engineering (Bogina et al., 2022). Also connected to knowledge about AI, Bochniarz et al. (2022) concluded that students' conceptualization of AI can significantly affect their attitude and distrust, which could be disproportionate due to science fiction, entertainment, and mass media (Kerr et al., 2020). Students and teachers have also reported ethical concerns about data privacy and control as well as how AI algorithms work (Freitas & Salgado, 2020; Bisdas et al., 2021; Holmes et al., 2022).

Exposure to EdAI tools, such as conversational agents (Guggemos et al., 2020), can change students' perceptions, with adaptiveness being essential for use intention. Practical experiences regarding EdAI tools can also change students' perceptions. For example, van Brummelen et al. (2021) showed an intervention where middle and high school students built their own conversational agents. Results showed a change in the students' perceptions (higher acceptance) after the intervention.

Recent qualitative studies have explored middle school students' conceptualization of AI (Demir & Güraksın, 2022) and HE student's attitudes and moral perceptions towards AI (Ghotbi et al., 2022), finding positive and negative aspects. Similarly, Qin et al. (2020) investigated the factors influencing trust in EdAI systems (mainly conversational agents) in middle and high school from several perspectives, including students, teachers, and parents. The authors identified trust risk factors as technology, context, and individual-related. Students and parents have expectations about the EdAI systems' potential to eliminate discrimination and injustice in education, which aligns with other studies. Seo et al. (2021) found that negative perceptions often come from positive aspects of AI, primarily due to unrealistic expectations and misunderstandings. The authors examined the impact of AI systems on student-teacher interaction in online HE, finding that while AI could enhance communication, concerns about responsibility, agency, and surveillance arose.

In the specific case of EWS, machine learning is applied to recognise patterns, make predictions and apply the discovered knowledge to detect students at risk of failing or dropping out by embedding predictive models (Casey & Azcona, 2017; Kabathova & Drlik, 2021; Xing et al., 2016). Predictions are delivered to the students through a traffic light signal and personalised automatic messages. When models are integrated within an EWS, students' retention and performance usually improve, and the students tend to express positive opinions (Arnold & Pistilli, 2012; Krumm et al., 2014; Ortigosa et al., 2019). However, teachers reported excessive dependence among students instead of developing autonomous learning skills and a lack of teacher-oriented best practices for using the EWS (Krumm et al., 2014; Plak et al., 2022). Qualitative studies offer findings regarding the dashboards provided by an EWS to detect students at risk of failing through semi-structured interviews conducted in small focus groups. These studies suggest that the students would prefer to see progress in percentages accompanied by motivating comments, as the rating scale was too simple (Akhtar, 2017). Also, students flagged as bad could be demotivated and their confidence could decrease, although they agreed about the importance of knowing performance status (Hu et al., 2014). Also, relevant, most papers focus on academic staff opinions (Gutiérrez et al., 2020; Krumm et al., 2014; Plak et al., 2022), indicating that more research is needed to capture students' perceptions to understand better the impact on their behavior, achievement, and skills (Bodily & Verbert, 2017).

Also tellingly, research on EdAI tools has primarily focused on developing them, conducting short experimental applications, and conducting surveys that do not relate to real classroom settings (Ferguson et al., 2016). These studies often rely on minimal exposure to the technology (Bochniarz et al., 2022; Gado et al., 2022; Seo et al., 2021) and focus on development and testing (Hu et al., 2014; Rienties et al., 2018), rather than the broader context of daily teaching and learning (Bodily & Verbert, 2017). In this context, critics argue that speculative and conceptual propositions for future EdAIs generate polarisation, leading to excessive enthusiasm or pessimism (Buckingham-Shum, 2019). Speculative studies cannot significantly contribute to data privacy and negative opinions about AI systems in society and education (Prinsloo et al., 2022). Contributions to exploring the subjective experience and understanding of EdAI tools can help promote a more balanced vision of human-computer interaction in education.

3. Methodological approach

From the background analysis, we considered two main research questions:

- RQ1: How do the students experience AI tools as an EWS, given their profiles, their self-efficacy when studying, their prior experience of AI tools overall, and their opinion on data ethics?
- RQ2: Are there differences between the students given their fields of study? Particularly: if a student is closer to the field of computer science relating to the development of AI tools, will the student be more confident and willing to adopt the tool?

Our study sets its methodological basis on the phenomenological understanding of human experience applied to human-computer interaction. We refer to the *Encyclopedia of Human-Computer Interaction*, which highlights that "our primary stance towards the world is more like a pragmatic engagement with it than like a detached observation of it […] we are [...] inclined to grab things and use them" (Gallagher, 2014, Ch. 28). Therefore, experience means action and giving meaning within the context of life, things, and the technology surrounding us. In this regard, EdAI tools do not pre-exist but need to be experienced, used, and understood, for "intentional, temporal and lived experience [...] is directly relevant to design issues". Consequently, the development of EdAI tools requires a deep understanding of the human experience in their usage.

3.1 Context of the study

Blinded university is a blinded nationality fully online university with relevant national and international trajectory. All educational activity occurs within its virtual campus, which is based on a proprietary platform. *Figure* 1 displays the dashboards to which students and teachers have access to follow the progress of what is called Continuous Assessment of Activities (CAAs). To learn more about CAAs and the outputs of our EWS see "Supplementary Materials".

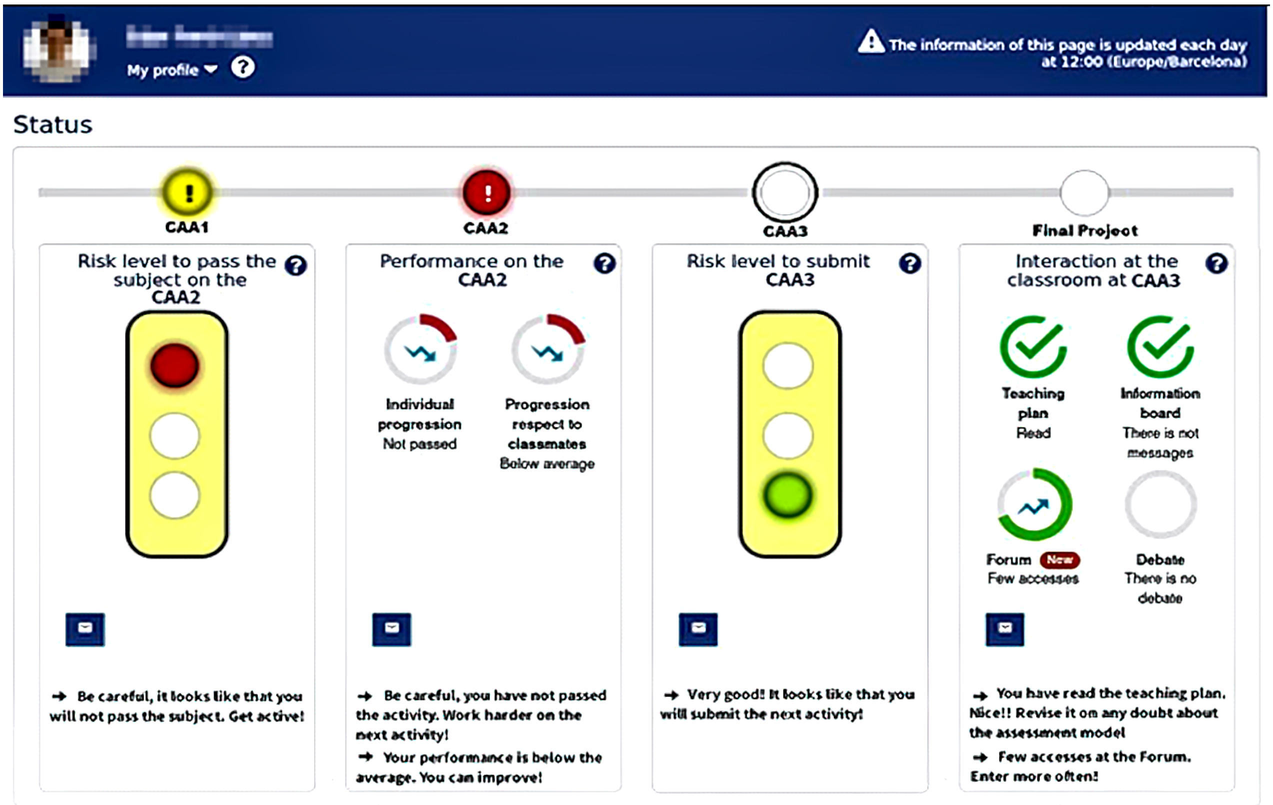

***Figure* 1. The student dashboard (status information). *Note:* AI-enhanced by the Editor to compensate for the inability to take high-resolution screenshots on the visualizing device (status of image quality not attributable to the Authors).**

3.2 Data collection method and participants

Blinded was tested during an initial survey carried out in the academic year 2020-21 across three different degrees (Computer Science or CS; Business Administration or BA; and Marketing and Market Research or MR). Out of 918 responses, 65 students were available to be interviewed. The interviews were held at the end of the course when only 51 students were available from the initial group due to dropout issues. Hence, we selected 25 students representing the overall characteristics of CS, BA, and MR courses, leading to 13 cases from CS, 10 from BA, and two from MR. We got replies from 24 of these students, and three did not attend the interview. Twenty-one students were finally interviewed. They were self-selected and engaged voluntarily with the activity according to the requirements defined by the blinded Ethics Committee. The interviews were conducted online using the videoconferencing system Blackboard Collaborate and recorded with the student's consent.

Table 1 reports the main participants' characteristics: degrees (CS, BA, or MR), age, expertise in the field of study, and working status were other relevant analysed characteristics. All participants had full-time jobs and pursued new studies to improve their career prospects as fully online courses. Despite their seniority as workers, some declared low expertise in the discipline field, which they were approaching for the first time. As for gender, twelve participants declared they were male, while nine declared they were female. Moreover, almost all CS students were male (only one female), and many BA and MR students were females (8 out of 11).

Student & Degree	*Age*	*Expertise*	*Gender*	*Worker*
BA1	30–39	High	Male	Yes
BA2	30–39	N.A.	Male	Yes
BA3	40–49	High	Male	Yes
BA4	40–49	Low	Female	Yes
BA5	Less than 25	Low	Female	Yes
BA6	30–39	High	Female	Yes
BA7	40–49	Low	Female	Yes
BA8	30–39	Low	Female	Yes
BA9	30–39	Low	Female	Yes

MR1	40–49	Low	Female	Yes
MR2	Less than 25	Low	Female	Yes
CS1	40–49	High	Male	Yes
CS2	Less than 25	Low	Male	Yes
CS3	40–49	High	Female	Yes
CS4	40–49	High	Male	Yes
CS5	50–60	High	Male	Yes
CS6	30–39	Low	Male	Yes
CS7	50–59	High	Male	Yes
CS8	25–29	High	Male	Yes
CS9	30–39	Low	Male	Yes
CS10	30–39	Low	Male	Yes

Table 1. Participants' characteristics. Acronyms adopted to characterise the degree: BA (Business Administration), MR (Marketing and Market Research), CS (Computer Science).

3.3 Data analysis method

The interview transcripts, duly revised by each researcher, were analysed using NVivo software. Thematic Analysis (TA) was later applied with a mixed deductive and inductive approach (called "codebook TA" by Braun et al., 2019). A set of codes was derived from the interview guide, which was composed of the following seven questions:

- Q1 – Q4, including age, the field of study, professional experience, motivation to study online, and academic self-efficacy;
- Q5, about the student's opinion of AI systems overall, and the specific issue of captured data, as contextualisation of blinded;
- Q6, asking about the students' expectations, interaction, and after-experience appraisal of blinded;
- Q7, inviting students' proposals for improving blindness.

Data were coded from the original verbatim transcriptions in Spanish, yielding a corpus of 21,761 words. Afterward, the data were read and segmented; all relevant excerpts of the interviews addressing aspects related to the interview scheme were marked and chosen for the analysis. A segment collected comments, descriptions, or opinions related to any of the questions in the interview, whether a single word, a phrase, or a longer text excerpt, thus composing a subtheme. New subthemes were coded from the initial themes and some logically complemented codes were added for specific codes upon researchers' agreement, e.g., "High Expectations" was complemented with "Low Expectations". This operation led to 17 themes with 67 subthemes from the seven initial themes, totalling 634 marked segments. If the segments included a reference related to two subdimensions in a way that was not separable, the excerpt was coded into both. This article is based on 11 themes and 52 subthemes, counting 396 coded excerpts over 12,046 words. The excluded themes dealt with issues outside the scope of this work, such as the like/dislike of online education and the motivations to pursue an online degree. The interview guide, the entire code tree, a table with exemplar excerpts translated to English, and the overall themes report in Spanish, extracted from NVivo and displaying the interrater agreement exercise, have been published as Open Data (Raffaghelli, Loria-Soriano, et al., 2022).

Data in Spanish were analysed using a code tree in English, which was discussed and enriched after coding two interviews as training. Two more codes were added after coding four other interviews. Five codes created logically (procedure above) were not used. The researchers translated and collected a representative sample of codes (10% or n = 63 out of 634) for each code and subcode to ensure the reliability of the analysis. The excerpts under the codings were examined in a consensus meeting, reaching a good agreement level for the themes (56/63, 89% agreement).

After consolidating the code tree with the themes that emerged, a content analysis was carried out. Content analysis (Elo et al., 2014) is a research method aimed at identifying, through quantitative means, the presence of certain words, themes, or concepts within some given qualitative data (i.e., text). After coding and detecting the themes in a text, the researchers can quantify and analyse such themes' presence, meanings, and relationships. In our approach, we adopted the NVivo tools for quantification and aggregation of themes and subthemes, represented in columns of *Tables 7 – 11* of the Supplementary Materials as:

- analysing the presence of coded themes and subthemes across the interviews (*n.int*)
- representing comparatively the coverage of themes and subthemes across interviews *(% cov.*)
- analysing the frequency and percentage of codes per theme (*Fr.codes, % codes*);
- analysing the number and percentages of words per theme and subtheme (*n.words, % words*);
- using the coloured rows to analyse the maximum theme representation across interviews (MTAI); the intercode frequency (IF) or the code for a theme, including all the subthemes, relating to the overall corpus; and representing comparatively the subtheme's coverage within a theme (% codes) as well as the coverage of words per subtheme (% words).

Overall, the frequency and comparisons of coded themes and subthemes across interviews showed the topic's relevance for several participants. Meanwhile, the frequency and comparisons of codes and words were used to show how densely the topic was represented across the participants and take the corpus extracted as a discourse sample.

4. Results

4.1 RQ1: Thematic and content analysis

At first sight, some themes got significant attention: the participants were particularly talkative when referring to blinded characteristics. As observed in *Table 7* (see Supplementary Materials"), the themes relating to the tool characteristics and UX (e.g., features such as the traffic lights, the relevance for future students, their interest and understanding of the tool) were covered on average in more than 52% of interviews. The specific subthemes most represented, based on the number of coded segments, were: comments on the emails sent by the intervention mechanism (42.03%, 16 interviews); the understanding of the tool (51.11%, 11 interviews), the experience of the green light (72.00%), which was the most frequent across 17 interviews; a high interest (87.80%, 17 interviews) and potential relevance for future students (81.58%, 14 interviews). In the students' expressions: "*I think the information –provided by blinded– is perfect. That is, what is measured and what we as students can see is perfect, at least from my point of view [BA3]*"; *"as a fairly good overview and fairly easy to understand, especially the traffic light" [BA6]*. Concerning the green light, all students were active and mostly received a green low-risk level throughout the course: *"I think they were green in general" [CS6]*.

Although they were much less frequent, 13.16% in five interviews pointed to low relevance as part of the UX, and 4.88% in two interviews had a low interest. In all cases, there were noticeable comments about a certain discontent with the tool's automated support: "*Of course, I already know that I have met the deadlines, that I have submitted the assignments, as well as what grades I received. Let's say that the prediction is pretty obvious*" *[CS10]*. The comments were related to good learners who did not see any at-risk lights (i.e., red or yellow): *"I wouldn't be able to tell you how exactly it has helped me. The only thing I am currently doing is checking from time to time if the light is green. That's all" [CS4]*.

Nonetheless, beyond the attention given to making proposals, we also found a certain diversification of the proposals with comments (see *Table 8* of the Supplementary Materials) on the panel display (36.36%, ten interviews); a tool able to provide deeper insights in intervention messages (31.82%, 12 interviews); and some attention to the overall design (10.61%, four interviews), the way the prediction was generated (13.64%, five interviews) and the possibility of access to a tutorial (7.58%, four interviews). For example, the students indicated that they would add specific features, like *"Maybe a graph? To see progress. Like 'you have started here, you have been gradually progressing and you are improving […]" [BA9]*. They also commented on deeper educational aspects: *"I would like to receive the professor's comment about my work, other than automatic comments because you can tell they are coming from the machine" [CS1]*.

Also, data capture and usage in education got relevant attention with a coverage of 61.90% (see *Table 9* of the Supplementary Materials). For example, a student said "*It is very important. I think that data nowadays is one of the most important things, reading data to be able to evaluate and to be able to make decisions and to be able to improve everything for the student, and this type of tool can help us indirectly to be able to pass the subject, which is our aim" [BA3]*, as a part of a proactive approach to share data that can be opened (see subtheme "Open-Proactive", 60.00%, 13 interviews). There were also more cautious voices: "*Well then. Well, in the end, it's moving forward. Yes, I don't see it as a bad thing, as long as they are used in an appropriate way, without unlawful uses […]" [BA6]* (see subtheme "Open-Cautious", 30.00%, eight interviews). Very few students agreed with the idea of opening restricted-access data, and with precautionary measures: *"You explain perfectly, they are using your data without you having given explicit and clearly informed permission, unlike blinded" [BA9]*. No students commented on the idea of capturing restricted data for any purpose.

As observed in *Table 10* of the Supplementary Materials, a theme that did not often appear in the students' responses was their expectations about being blinded (28.57%). If we observe the specific expressions, the subtheme "LowExpectations" was mainly represented within the six interviews in which it appeared. This is an interesting element if considered together with the relatively good opinion expressed as part of the UX, which could be deemed consistent with the disconfirmation effect (Bhattacherjee & Premkumar, 2004), although further intracase analysis of this relationship should be necessary. It is worth commenting that the students had little experience in AI systems. The subtheme AI experience was covered in seven interviews for automated educational tools (40.00% of codes); image processing in three (20.00%); recommender systems in seven (32.00%), and chatbots as tutors in only two (8.00%).

Finally, we observed that the participants, all experienced workers and primarily middle-aged, felt generally confident about their study methods (see *Table 11* of the Supplementary Materials). They expressed high or very high confidence (15 interviews) in 52.38% of the overall discourse. Nonetheless, expressions highlighting less confidence were also present, but to a lesser extent (22.86% in three interviews, neither low nor high, and 25.71% in five interviews, expressed low confidence). Confidence is an interesting personal trait that can be considered when understanding the approach and acceptance of AI tools. Cross-tabulating data, we expected to see expressions of less confidence co-occurring with less openness to accept new and unknown technological tools.

4.2 RQ2: Cross-Tabulation

To grasp the nuances of the students' experience with the system, we decided to analyse the discourse considering the different students' fields of study. Therefore, we cross-tabulated the results for the relevant themes that emerged.

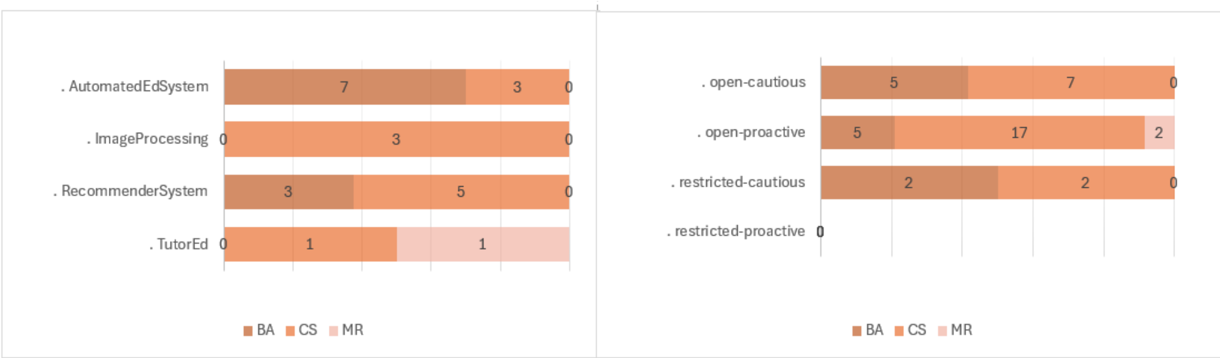

Figure 2. AI experience and Data capture and usage by field.

Overall, we observed that the CS students had a more diversified experience of EdAI systems relating to their peers from BA-MR (*Figure* 2, left). Also, they were more positive concerning data capture and usage (*Figure* 2, right), and they generally had higher self-efficacy in academic tasks (*Figure* 3, left). The categories overlapping must be noticed, with 9 out of 10 CS students being males and BA-MR prevalently females (8 out of 11 cases). We cross-tabulated gender and self-efficacy to study this phenomenon further, and we confirmed that males across disciplines expressed a higher self-efficacy ("High" with 3 BA and 8 CS, and "Very-High" with 2 CS) than their female peers ("High" with 3 BA, and "Very-High" with 2 BA). In their words: *"I like the subject (but) I have had to get a private teacher to help me […] because it is impossible, not even with a thousand tutorials could make it and it is getting very hard for me" [MR1]*. *"I try when I have a holiday at work, I spend the whole morning, all the time I have free in front of the computer, looking at notes and applying them, doing exercises, trying to apply everything […] to see if I can assimilate (the course's content)" [BA9]*. Still, the male students from CS were the only group to express low self-efficacy (4/9 codes for gender and 35 coded segments on self-efficacy), highlighting the possibility that the perceived difficulty of the subject studied also has implications for self-efficacy.

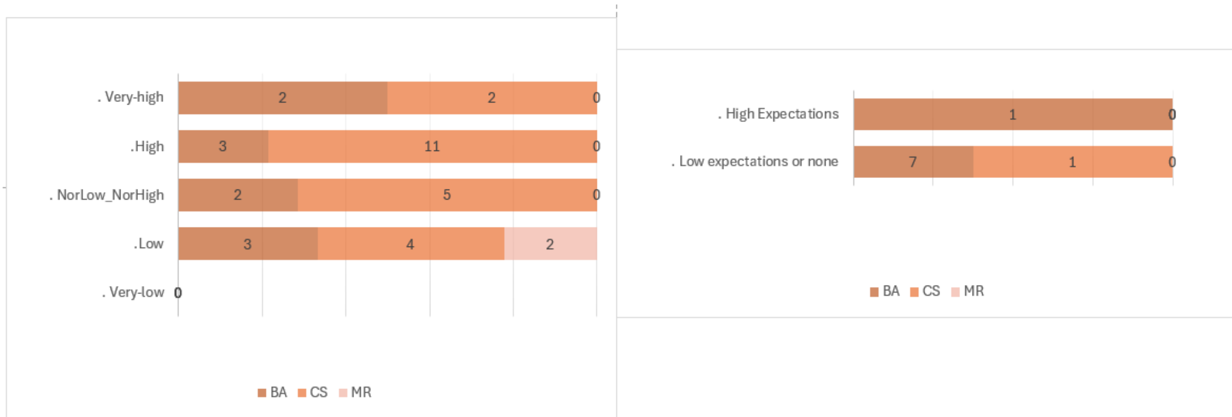

Figure 3. Self-efficacy and Expectations by field.

Concerning their expectations, independently of the student's background, they did not clearly envision blinded nor consider it relevant at the beginning (*Figure* 3, right). However, after the experience, we observed that those taking part in most of the interaction (*Figure* 4, left) were the CS students who showed a higher interest (UXI prefix, 24/36 codes) and saw more relevance (UXR prefix, 18/31 codes) in their experience of the tool. Nevertheless, the BA students displayed good values concerning the UX within their own group, with high relevance (13/13 codes in that category) and interest (11/12 codes).

Understanding the tool was a bit more controversial in all fields. BA students show a high understanding with ten codes on one hand, but they also express a low understanding with six codes (16 in total). The situation is similar for the CS students, with 12/21 codes for high understanding and 9/21 for low understanding. Overall, the students tended to refer more to a high or middle understanding (27 coded segments of 43, 62.79%) than to a low understanding (16/43, 37.20%). For example, a CS student referred to a high understanding describing the functions and their impact: "*And they also tell me the points where I'm doing better […] Well, the tool showed that I did the minimum required. So I think OK, today I can improve. It's like direct feedback, without having to constantly bother the teacher" [CS2]*. But low understanding is also referred to by both CS and BA-MR students *"If it is a totally new application, then it does give you some idea of at least the positioning to know what I'm going to find" [CS10]*; *"What I didn't quite understand, is the bottom part of the tool that I had, like the note that appeared like it was always on the first CAA, and I didn't understand how to changing it, or if it could be changed or if it was a graphic in general" [BA8]*.

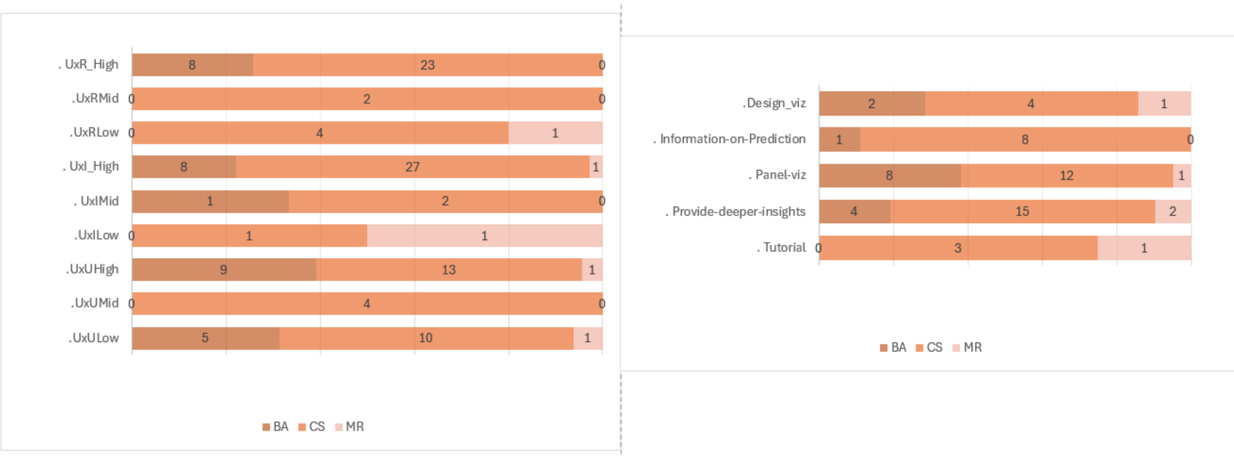

Figure 4. Relevance, interest, understanding and Proposals by field.

Finally, the students were highly proactive in making proposals and suggestions to improve the tool (covered in 12 interviews), as *Figure* 4 (right) shows. However, the crosstabs revealed a prevalence of suggestions from CS (42 coded segments out of 62, 67.74%) and male students (38/62, 61.29%). Particularly, they made suggestions in several categories: integrating a tutorial (3/4) to provide deeper insights (15/21); changes to the panel visualisation (12/21); enriching the source of prediction (8/9); and improvements to the overall blinded design (4/7). It is interesting to see, nonetheless, that both CS and BA-MR students made suggestions relating to the tool's appearance and impact on the learning process: *"I would add one thing [...] not only the tool should tell you if you've not logged in to the forum, but it should also look at the interactions that you have on the forum, because I, for example, log in a lot, I read everything, but I interact very little. So maybe interacting can be useful to promote better learning" [CS10]*. *"I would add an orientation like when you are like 'I don't know which way to go or how you would recommend it', to see how I have evolved or how different students have done, how they have done one thing or another" [BA7]*. Instead, only the CS students were more concerned about how the tool worked and how the data captured could be used more effectively: *"Talking about trying to incorporate as many parameters as possible to give a prediction, that could be maybe a bit more concrete and more useful. Because the comments I got were keep working, so you're going to do well in the subject […] but I need more" [CS8]*. In this regard, males' and females' suggestions tended to coincide with more suggestions for the panel visualisation (11 female-coded segments compared to ten from males) and provide deeper insights (8 and 13 respectively). Consistently with the subject field, only males referred to the predictive system (9 coded segments out of 62).

5. Discussion and conclusion

EdAI systems like EWS are becoming more common in HE, usually studied in development settings instead of analysing the students' reactions (Ferguson et al., 2016) and Bodily & Verbert (2017). Our investigation analysed students' perspectives on EdAI tools integrated with the learning-teaching process in undergraduate courses at a fully online university. Through 21 semi-structured interviews, the researchers explored students' experiences regarding the tool, expectations, and suggestions for improvement. The results revealed that students, mostly senior workers with good academic self-efficacy, had little experience with EWS on artificial intelligence systems in education and low expectations. The usage experience triggered interest and reflection on the EWS tool and data usage. This enriched the participants, prompting interest and supporting them to reflect on the EWS features and design.

Regarding RQ1, we observed relevant insights. First, the analysis corroborates the findings of (Raffaghelli, Rodríguez, et al., 2022) about the disconfirmation effect (Bhattacherjee & Premkumar, 2004). This also reveals an inverse relationship between students' expectations about technology and their acceptance behavior. This is relevant when considering the positive UX opinions expressed by students (as in Hu et al. (2014)). Thus, as stated in Akhtar et al. (2017) and van Brummelen et al. (2021), using EdAI tools implies changing perceptions and opinions.

In response to the collected data, the students' perspectives on data privacy reflected the growing societal awareness of the issue (Prinsloo et al., 2022). A notable finding was that a majority of students expressed little concern about the use of their data, particularly if it contributed to their well-being or technological progress. This finding was different from Bisdas et al. (2021), where the students reported ethical concerns about privacy and algorithmic control over the data, indicating a potential influence of the participants' medical training background on their views. Our results align with existing literature, such as Bochniarz et al. (2022) and Kerr et al. (2020), which highlights the connection between knowledge and attitudes towards Educational AI (EdAI), along with the associated feelings of distrust or trust (Ghotbi et al., 2022). However, as in Akhtar et al. (2017) and Guggemos et al. (2020), we also showed how exposure to an EdAI could trigger the students' engagement in making concrete proposals to shape their relationship between humans and technological-educational agents.

Students' suggestions on the panel display and intervention messages showed misunderstandings about the panel's usefulness because all students received a low-risk level (i.e., green traffic lights). A similar limitation was observed in intervention messages since students only received appraisal messages. Positive effects were found in other studies related to the EWS opinion about messages (Arnold & Pistilli, 2012; Bañeres et al., 2021; Raffaghelli, Rodríguez et al., 2022) on at-risk students who received recommendations and guidelines (Seo et al., 2021), but not in this work. For this reason, students requested training and tutorials to better understand the EdAI (Kim et al., 2020).

Concerning RQ2, the study analysed gender differences (more males in CS and more females in BA-MR) in the acceptance of EdAI tools among different disciplines. CS students showed higher confidence and expectation in the system, while BA-MR students were less confident in its usage. Low perception of usefulness and ease of use may affect usage (Chen et al., 2021; Rienties et al., 2018). However, EdAI acceptance is based on the perceived knowledge of the tool (Gado et al., 2022), which might be the case for the female participants. Therefore, students' perceptions of the instrument seem deeply rooted in their understanding and needs as students and future professionals. CS students' deeper understanding of the system leads to more engagement and curiosity. However, BA-MR students converged with CS peers in discussing features that support academic activities.

The lower self-efficacy in academic tasks displayed in our study by the female students might also be caused by lower self-efficacy in relation to technologies (González-Pérez et al., 2020; Sáinz & Eccles, 2012; Zander et al., 2020). On the other hand, females with higher self-efficacy are more engaged and critical about tools supporting their studies.

BA-MR students have a "reactive and cautious" opinion about data capture, while CS students are more focused on the benefits of data sharing. This may be due to their knowledge of internal EWS operations and their scepticism about the potential benefits.

This study has significant limitations. There were only 21 self-selected white students from the Global North, and their post-digital positioning may have been influenced by positive experiences in technological settings. Moreover, our research also needs to consider differences across disciplines and gender. The study found that students with better performance and a preference for innovative learning tools received low-risk predictions, but the study did not provide insights into at-risk students (Akhtar et al., 2017). Gender enrolment also influenced the findings, with some findings more related to disciplines than gender.

Overall, these results emphasize the importance of supporting students' understanding and experiences of EdAI systems to participate in the development of these tools, aiming for quality, relevance, and fairness. Teachers' perspectives are also crucial, as seen in Krumm et al. (2014) and Plak et al. (2022). Moreover, as Buckingham-Shum (2019) highlights, the debate on data usage should be opened to both students and teachers to ensure they feel empowered by using EdAI tools. Prinsloo et al. (2022) propose a complex approach to data privacy, focusing on alternative understandings of personal data privacy and their implications for technological solutions. However, understanding central and alternative approaches to data privacy is crucial for an ethical approach to EdAI tools (and in our specific case, to the EWS). This idea is based on "postdigital positionings," which refer to the unique way individuals relate to the emerging technological landscape (Hayes, 2021, p. 49). Therefore, empirical studies should consider students' lived experiences, teachers' experiences, and intersubjective perspectives on technology (Pedró et al., 2019; Rienties et al., 2018). This spectrum requires further exploration, to understand the impacts of EdAI, the social and educational implications, and the balance between the design, development, and human impact of EdAI.

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