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Applying the UTAUT model to explain the students' acceptance of an early warning system in Higher Education

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ABSTRACT

Artificial intelligence systems such as early warning systems are becoming more common in Higher Education. However, the students' reactions to such techno-pedagogical innovations are much less explored in settings beyond the development and testing. This paper analyses the students' acceptance of an early warning system developed at a fully online university. Following a pre-usage and post-usage experimental design based on the Unified Theory of Acceptance and Use of Technology model and the Structural Equation Modelling, we observed how, within four courses (839 participants in the academic year 2019–20, of which 347 participants answered both a pre- and post-usage questionnaire), the students' acceptance changed overtime. Our findings revealed a disconfirmation effect in the acceptance of the early warning system, namely, a difference between expectations surrounding the technology pre- and post-usage, and shed light on the ways artificial intelligence systems should be integrated within Higher Education virtual classrooms.

1. Introduction

Artificial Intelligence (AI) is growing in all sectors of human activity, given the availability of data and the possibility of processing them in real-time. Higher Education (HE) institutions are not an exception and are investing much effort into enhancing personalised support for their students through AI techniques. In this regard, there is a growing field of research and practice connected to educational data mining and the so-called learning analytics (Siemens & Baker, 2012), which results in several techno-pedagogical developments integrated into what we could call intelligent virtual classrooms to provide personalised support (Viberg, Hatakka, Bälter, & Mavroudi, 2018). Nonetheless, the outputs are diversified and entail several debates on the educational stakeholders' perceptions, acceptance and impact of these technological developments.

A clear example of this trend relates to what is has been denominated Early Warning Systems (EWS). These automated instruments aim at warning the students and their teachers about specific situations. Frequently, the EWS also provide an intervention mechanism that helps teachers provide early personalised guidance and follow up to the students to amend possible issues. EWS can be placed in the context of learning analytics that tries to predict the students' behaviour individually based on historical and current data to provide relevant and personalised information to both students and teachers, supporting data-driven decision-making (Ferguson,

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2012).

However, when an EWS is deployed in real educational settings, several problems may arise, from technological (i.e., integration, scalability, security breaches, among others) to user engagement and intention to use in the future. In this sense, the issues that might arise are related to the overall user experience, the cognitive processes triggered by interfaces and visualisations, privacy, ethics, and user misconceptions (Nunn, Avella, Kanai, & Kebritchi, 2016). Technology experts can handle the former, but the latter requires careful analysis and interdisciplinary interventions that span from users' digital literacy to software redesign (Selwyn & Gašević, 2020). In this regard, technology acceptance is one of the most widely used approaches to studying the cognitive and social aspects addressing the users' expectations, including the users' understanding of the technology to be used to its full potential. Though the approach has been widely adopted, the studies on AI systems in education are very recent (Scherer & Teo, 2019).

Therefore, our study delves into the factors connected to students' acceptance of an EWS (Bañeres, Rodríguez, Guerrero-Roldán, & Karadeniz, 2020; Karadeniz, Bañeres, Rodríguez, & Guerrero-Roldán, 2019) developed within an institutional project (named LIS) at the Universitat Oberta de Catalunya (UOC). Moreover, we also explore how acceptance changes over time, following a pre-usage and post-usage experimental design based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh, Morris, Davis, & Davis, 2003). UTAUT has been selected for being a robust model, vastly used to analyse technology acceptance in several domains, including education (Ibrahim & Jaafar, 2011; Lin, Lu, & Liu, 2013; Thomas, Singh, & Gaffar, 2013; Wong, Teo, & Russo, 2013). We also used Structural Equation Modelling (SEM) to analyse the relationship between pre-usage and post-usage according to the UTAUT model. The EWS was tested in four undergraduate courses at the UOC during the Spring semester of the 2019–2020 academic year. The number of students who consented to participate was 839, of which 347 students answered both the pre- and post-usage questionnaires.

Our findings reveal a disconfirmation effect (Bhattacherjee & Premkumar, 2004) in accepting the EWS, namely, a difference between the technology usage expectations (the EWS) and the post-usage experience. This type of longitudinal study is not frequent in educational technologies (Scherer & Teo, 2019). They can be of interest to researchers and practitioners involved in developing and using advanced educational technologies based on AI, which may represent a source of societal change in HE, independently of its educational delivery model (blended or online).

This work is structured as follows: Section 2 provides the relevant background about EWS, technology acceptance models and the expectancy-disconfirmation theory to model how users' expectations of technology change over time. Following this, Section 3 presents the materials and methods followed in the research. The results are shown in Section 4. Finally, Section 5 provides a discussion, while Section 6 draws the conclusions and suggests future research opportunities.

2. Background

2.1. Early warning systems

EWS are an example of tools to guide the students better and monitor their progression by identifying students at-risk of failing. The most referenced work on EWS is Course Signals at Purdue University (Arnold & Pistilli, 2012), where students' performance in their courses was monitored. The tool provided student and teacher dashboards, implementing different intervention mechanisms ranging from sending messages to face-to-face meetings with them. The tool's advantages were clearly shown, i.e., better retention, real-time monitoring, and student satisfaction.

There are different types of EWS depending on the focus of at-risk detection: dropout on face-to-face environments (Knowles, 2014; Márquez-Vera et al., 2016), dropout on online courses (Lykourentzou, Giannoukos, Nikolopoulos, Mpardis, & Loumos, 2009; Srilekshmi, Sindhumol, Chatterjee, & Bijlani, 2017; Xing, Chen, Stein, & Marcinkowski, 2016), or early detection of students at-risk of failing (Casey & Azcona, 2017; Falkner & Falkner, 2012; Macfadyen & Dawson, 2010; Vandamme, Meskens, & Superby, 2007). As stated by different authors (Bañeres et al., 2020; Freitas & Salgado, 2020; Ortigosa et al., 2019), many of the developments of EWS focused on defining predictive models to identify such at-risk situations (Cerezo, Sánchez-Santillán, Paule-Ruiz, & Núñez, 2016; Huang & Fang, 2013; Kabra & Bichkar, 2011; López-Zambrano, Lara, & Romero, 2020), and few developments can be found. However, the number of developments applied in real educational settings has been increasing during the past years. Some systems only focus on showing dashboards for teachers (Krumm, Waddington, Teasley, & Lonn, 2014; Najdi & Er-Raha, 2016; Wolff, Zdrahal, Herrmannova, & Knoth, 2014) following the learning analytics tradition. Others also provide information for students (Bañeres et al., 2020; Hu, Lo, & Shih, 2014; Ortigosa et al., 2019) since it is critical to make each stakeholder group feel informed and empowered.

2.2. Technology acceptance

Several models have been developed to analyse how users come to accept and intend to use technology. Such models are based on the Theory of Rationed Action or TRA (Ajzen & Fishbein, 1977), which addresses the idea that the users' actions are determined by the rational evaluation over their expectations on such actions. Therefore, the subjective set of beliefs are crucial at the time of configuring expectations.

The UTAUT model integrated the main relevant models in the nineties (notably the TAM, Technology Acceptance Model), considering the relevance of social influence on expectations and usage (Venkatesh et al., 2003). It consists of four constructs (i.e., effort expectancy, performance expectancy, social factors, and facilitating conditions) and four moderating variables (i.e., age, gender, education, and voluntariness of use). The constructs, combined with different moderating variables, directly affect behavioural intention evaluation (Venkatesh et al., 2003).

The UTAUT model has been vastly used to evaluate technology acceptance (Williams, Rana, & Dwivedi, 2015). In the past years, AI brought new products to the market. Gadgets, services, and systems are ready to be used for the customers. In education, AI is being used in terms of predictive analytics, recommenders, or automated chatbots. The UTAUT model has also been used to evaluate such technologies, i.e., predictive analytics (Brünink, 2016), recommenders (Wang, Luse, Townsend, & Mennecke, 2015), and chatbots (Kim, Jo, & Lee, 2019).

The contemporary critiques to TAM and UTAUT models applied to AI should also need to be considered. Recently, Kessler and Martin (2017) have pointed out that the hedonic factors associated with acceptance in prior literature were less important than data security, compatibility and relationship with the type of device when coming to use IoT and AI. Such technologies' very recent uptake might imply little understanding and minimal end-user AI experience (Kessler & Martin, 2017; Lancelot Miltgen, Popovič, & Oliveira, 2013). Users' expectations may also be oversized due to science fiction, entertainment and mass media press and the political agendas connected to AI (Kerr, Barry, & Kelleher, 2020). In this regard, the exposition and development of acceptance might offer a more accurate picture of how the users engage with AI tools and services.

Finally, the overall adoption of UTAUT as a theoretical foundation for our modelling must be critically considered. Though technology acceptance is a consolidated area of research, there are open debates around deterrents and contradictions. In the educational technologies field, there are open debates around the generalizability and validity, particularly considering the divergent cultural contexts, participants and technologies under analysis (Scherer & Teo, 2019). Tellingly, as Lim (2018) reported, certain types of technology acceptance research should be avoided since they do not provide any new insight while others are still relevant. Amongst the latter, the author considers different combinations of propositions and methodological procedures and/or research project's impact in research and practice, which "are encouraged for their conceptual development and extension, generalizability, and rigor" (p. 8). As also explained in the background, the rising concern around AI is generating a new strand of research on the acceptance of such technologies. Therefore, our application of UTAUT furthers the understanding of the impact of AI systems on education.

2.3. *Expectancy-disconfirmation theory: a longitudinal focus on acceptance*

The problem of changes over time in the users' expectations after more or less intense exposition to technology was analysed by Bhattacherjee and Premkumar (2004). Their work was based on the Expectation Disconfirmation Theory (EDT) as an extension of the Cognitive Dissonance Theory (CDT) formulated by Festinger (1957) in the field of social psychology. Its main application is related to consumers' satisfaction, connecting the consumers' expectations over a product or service and their actual intention to purchase after a short usage period. In IT usage, it was suggested that users' pre-usage beliefs or attitudes (as cognitive elements) are often unrealistic if the user has never been exposed to technology. The *delta* between the user's excessively positive or negative idea over technology and the opinions after having experienced it has also been confirmed in the studies adopting longitudinal approaches (Bhattacherjee & Premkumar, 2004; Johnson, Zheng, & Padman, 2014; Xu, Abdinnour, & Chaparro, 2017). Theoretically, it is plausible to observe a negative relationship between an initial state and exposure to a service, product or technology: the higher the expectations, the lower the satisfaction. Empirical studies (Yi, 1990) have reported diversified situations. For example, Johnson et al. (2014) report that if a technology is adopted several times, the users might have the opportunity to adapt themselves, improving their final opinion. However, users prone to adopt more technology have higher expectations (Ashraf et al., 2020; Thong, Hong, & Tam, 2006).

The studies in education cover a wide range of technological applications, from mobile phones (Almaiah, Alamri, & Al-Rahmi, 2019; Hoi, 2020), to clickers (Cheung, Wan, & Chan, 2018) to more complex constructs like blended learning that mixes pedagogical and technological elements (Chen, 2011; Dakduk, Santalla-Banderali, & van der Woude, 2018). More recently, the acceptance of incipient tools based on AI systems have been analysed (Guggemos, Seufert, & Sonderegger, 2020; Rienties, Herodotou, Olney, Schencks, & Boroowa, 2018). However, in all the mentioned studies and after screening the related literature, the acceptance questionnaire was applied in a single session with minimal, theoretical or self-reported exposure to the technology.

3. Materials and methods

3.1. *Experimental context*

As a fully online university, all the interactions at the UOC occur within its own virtual campus. Courses are organised in virtual classrooms attended by affiliated teaching staff coordinated by faculty member staff. The university provides a flexible, student-centred model since most students work and/or are adults with families. The model is based on access to resources, exercises and continuous assessment activities. The latter are graded with the following qualitative scale: A (very high), B (high), C+ (sufficient), C- (low), D (very low), where a C+ is the minimum passing grade. Grade N (non-submitted) is used when a student does not submit the assessment activity.

Students' performance in the continuous assessment is intimately correlated with students' success, impacting the retention rates (Grau-Valldosera, Minguillón, & Blasco-Moreno, 2019). This is especially relevant in the first semesters of undergraduate courses. Precisely, the software engine behind the EWS within the LIS project (Karadeniz, Bañeres Besora, González, & Guerrero Roldán, 2019) is a predictive model which forecasts whether the students have chances to fail the course. In such a case, the EWS identifies them as at-risk students. The predictive model (Bañeres et al., 2020) is trained and validated before the course starts using historical data of students that have enrolled in the past and likely share characteristics with future students. The predictive model considers several features about the students. Concretely, the students' grades obtained for the already graded assessment activities; the number of courses (and credits) the students have enrolled in; whether they are a new student at the university; how many times the students have enrolled in the course, and their grade point average which measures how well the students scored at the university.

The prediction is summarised in a Green-Amber-Red semaphore (similar to Arnold and Pistilli (2012)) that warns each student of her warning classification level and considers the student's performance and the prediction accuracy. A green semaphore represents that the student is not at-risk (good performance and the prediction has a good accuracy). Amber means the student is in an intermediate situation (performance lower than desired or low prediction accuracy). Finally, a red semaphore signal indicates a high likelihood to fail (poor performance and the prediction is accurate enough). Although providing the student with information about her chances of failing (or conversely passing) after an assessment activity has been graded may be helpful, it is not enough. The EWS also provides the student with information about the performance she should achieve to move past the at-risk situation in the next activity. All this information is provided via a dashboard (see Fig. 1).

Also, students receive personalised messages as an intervention mechanism embedded in the EWS. Messages are triggered when certain events and conditions hold. Messages may include informational and goal setting (to be sent, for example, when a new assessment activity starts), reminders (for example, to inform students that a deadline is approaching), or feedback when an assessment activity is graded. In the latter case, the message also includes explanations about the issued prediction and the assigned warning level, recommendations and guidance for the upcoming assessment activity, especially for those at-risk (i.e., the messages are adapted depending on the students' situation and profile).

3.2. Research design

Our study aimed at getting a longitudinal picture of the changes in technology acceptance. The research question we formulated to that end was:

RQ. When using an EWS (such as PINBALL), how does the acceptance level of learners change over time?

We postulated a two-stage model applied to the students' experience with the EWS developed in the LIS project to answer this question. However, several subsidiary steps were arranged within the research design in order to achieve the final aim.

Firstly, we defined the type of technology that we expected acceptance for. In this regard, acceptance of the EWS is deemed an innovative technology integrated into an e-learning environment. The students' behaviour (the interactions with the EWS and perception of impact on their learning process) is viewed as the result of a set of beliefs about the technology and the entangled set of affective responses. Therefore, a tailored UTAUT questionnaire might analyse the development of acceptance. Specifically, we adopted an extended version of the UTAUT model to structure the variables connected to the construct of acceptance. Consistent with the UTAUT model, we included all the dimensions measuring the EWS acceptance: Perceived Usefulness (PU), Expected Effort (EE), Social Influence (SI), Facilitating Conditions (FC), and Trust (T).

Fig. 2 summarises the experimental procedure. We established a procedure for acceptance evaluation in two stages. We deployed

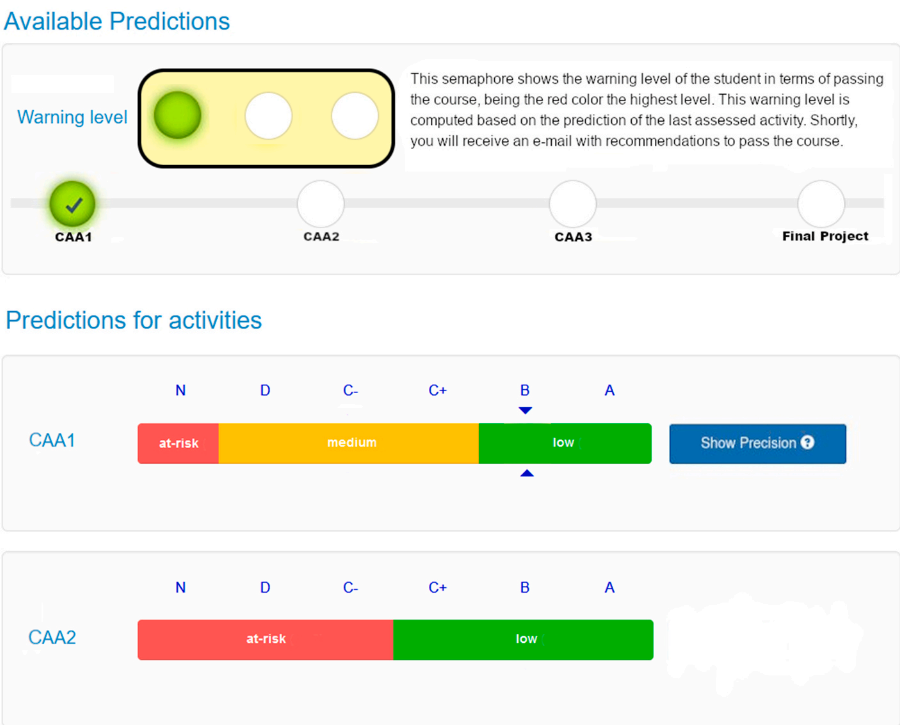

Fig. 1. The student dashboard.

an initial stage of acceptance evaluation, where the students' experience was null (pre-usage stage) since they had not been exposed to the EWS. Then, a post-usage stage of acceptance evaluation was deployed at the end of the semester when the students had already experienced the EWS.

It is worth noting that the testing and evaluation of new software tools in courses require the Ethics Committee's approval. This committee imposes two main rules. First, participation is voluntary, i.e., students provide informed consent after reading the description, purpose, and data collected by the piloted tool. Second, the research must guarantee the anonymity of the responses obtained through questionnaires.

As for the UTAUT components included in our design, perceived usefulness and perceived effort were included as the most frequent predictors of acceptance in overall literature (Williams et al., 2015) and the specific literature on educational technologies (Scherer & Teo, 2019). However, the facilitating conditions were deemed extremely relevant due to the induced, not autonomous usage (namely, the EWS integration into the virtual learning environment). It is plausible that the students expect several forms of support embedded in teaching and tutoring activities. Moreover, we also considered social influence a good predictor of acceptance based on the literature connected to peer-learning, social learning and students' informal activity to support each other in HE (Räisänen, Postareff, Mattsson, & Lindblom-Ylänne, 2020). When interacting with AI tools, privacy concerns and dysfunctional system performance have been connected with low trust (Lancelot Miltgen et al., 2013). As a result, including trust as a UTAUT dimension was deemed relevant. The H1 and the H2 related hence the pre and post usage separately. Instead, the H3 was the most relevant, exploring the longitudinal relationship. We expected that perceived usefulness and effort expectation would have been the most sensitive to the disconfirmation effect. In this sense, whether the initial beliefs were enthusiastic or reluctant, a negative relationship with the user experience could be expected. Instead, social influence and facilitating conditions would change eventually due to social interactions and pedagogical activity. As most linked to ideals and values, the trust could remain stable, hence less exposed to the disconfirmation effect. Moreover, distrusting the data-trace methods is a sensitive issue amongst many users (Kessler & Martin, 2017; Lancelot Miltgen et al., 2013); experiencing the tool and seeing how data are collected might have a relevant impact on the users' trust in AI systems. Finally, the longitudinal analysis in the model was justified due to the need of exposing the students to the EWS as an intelligent, emergent technology and measure the differences on acceptance.

Fig. 3 introduces our model, which is based on the following hypothesis:

- H1: PUx, EEx, SIx, FCx and Tx (pre-usage) influence the acceptance of the EWS before usage.
- H2: PUy, EEy, SIy, FCy and Ty (post-usage) influence the acceptance of the EWS after usage.
- H3: An effect of disconfirmation will be found between PUx, EEx, SIx, FCx, Tx (pre-usage) and PUy, EEy, SIy, FCy and Ty (post-usage).

3.3. Instruments

A modified version of the UTAUT questionnaire was adopted in this study. The five dimensions were adapted, focusing on the specific technology under evaluation, the EWS. The questionnaire had a total of 22 questions: three to profile the participants

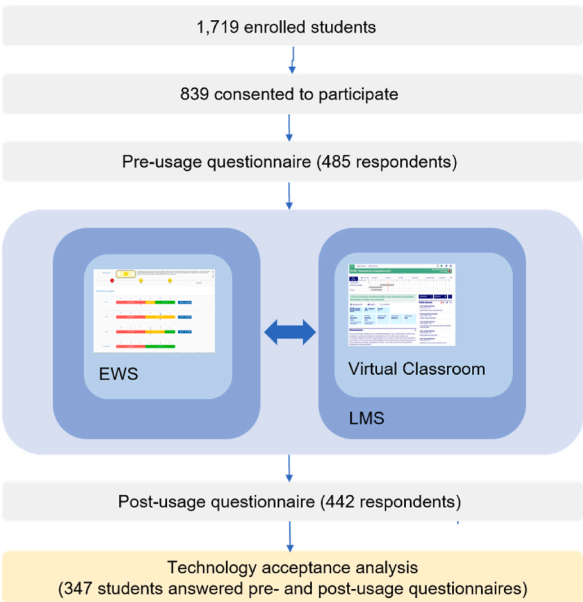

Fig. 2. Experimental procedure.

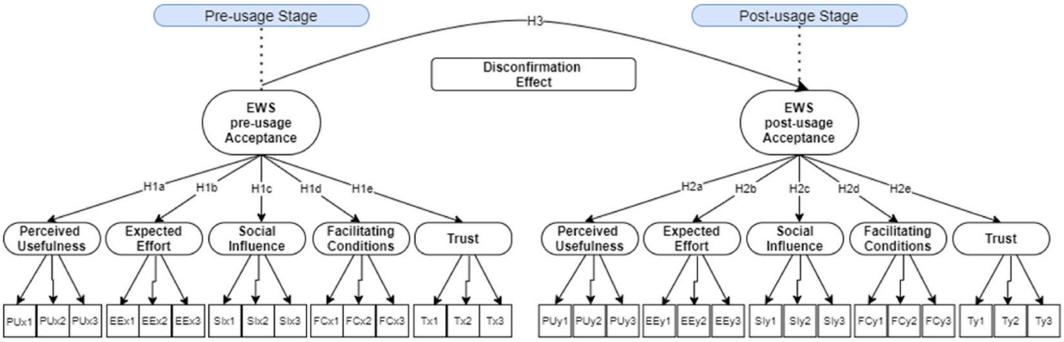

Fig. 3. EWS acceptance.

(discipline, age, gender); two open questions to explore other prior experiences and further thoughts on the system; and 15 questions based on the UTAUT model. Each question offered a 7-points Likert scale, from Strongly Agree (1) to Strongly Disagree (7). The pre-usage questionnaire was opened with a paragraph explaining what an EWS was and how the EWS developed at the LIS project (called PINBALL for the students) was implemented within the virtual classroom. This information was the base to trigger students' beliefs over technology. The questions were formulated in conditional/future form. The post-usage questionnaire had the same structure, but the questions were formulated in the past tense. The initial opening paragraph recalled the terms of the experience with the system. Annexe 1 introduces the pre-post usage UTAUT questions adopted in the survey.

As for the procedures, the questionnaire was sent as an online survey adopting the platform Qualtrics™, which offered a responsive version and immediate access to the datasets. Students who consented to participate in the study received a personalised URL to the questionnaires in their institutional email, which allowed us to correlate the same student's answers in the pre- and post-usage questionnaires. Students' responses were processed anonymously. The pre-usage questionnaire was sent at the beginning of the semester, while the post-questionnaire was sent at the end of the semester. The study took place in the Spring semester of the academic course 2019–2020.

3.4. Participants

Four mandatory first-year courses were selected, attending the importance of detecting and supporting at-risk students in the early stages of their degrees (Grau-Valldosera et al., 2019). Specifically, two courses belonged to the Faculty of Computer Science, Multimedia and Telecommunication, and the other two to the Faculty of Economics and Business. All the students were invited to participate in the study at the beginning of the semester. They received information about the characteristics of the EWS and the different phases included in the study through the virtual classrooms. As detailed in Fig. 2, students received the invitation to answer the pre-usage questionnaire after consenting and before using the EWS. The post-usage questionnaire was distributed at the end of the semester once the students had gained experience using the EWS. Answering the pre- and post-usage questionnaires was voluntary, although students received a kindly reminder. All the students who consented used the EWS in their courses.

To sum up, 839 students agreed to participate in the study (48.81% of the invited learners). Participation rates per faculty over invited students were reasonably balanced (59.92% from the Faculty of Computer Science, Multimedia and Telecommunication, and 44.54% from the Faculty of Economics and Business). Table 1 shows the questionnaires' participation by faculty and the total figures. Students who replied to the pre-usage questionnaire were 485, and the post-usage questionnaire was 442. A total of 347 students answered both the pre- and post-usage questionnaire, representing a rate of 43.65% of the students who consented to participate in the pilot. As for the missing data, eight learners in the pre-usage questionnaire did not declare the faculty (it was an open question, and learners wrote down nonsense character strings). In the post-usage questionnaire, we did not know the faculty of 95 participants because they did not answer the pre-usage questionnaire.

Gender participation in the pre- and post-usage questionnaires was imbalanced (34.87% of female versus 64.55% of male students; 0.58% of students did not provide information). This issue cannot be attributed to the study itself but to women's low presence in STEM fields (Fényes, 2015; UNESCO, 2017). Concerning the age of students who answered the pre- and post-usage questionnaires, it is

Table 1
Participation in pre- and post-usage questionnaires.

		Computer Science, Multimedia and Telecommunication		Economics and Business			
UTAUT questionnaire	Non-avail.	No. Students	Partic.	No. Students	Partic.	Total participation	Total participation (over consented)
Pre	8	164	33.81%	313	64.54%	485	61.01%
Post	95	141	31.9%	206	46.61%	442	55.60%
Pre and Post		142	40.92%	205	59.08%	347	43.65%

Table 2
Descriptive statistics, and scales reliability (Cronbach Alpha, Composite Reliability).

Items	PU1	PU2	PU3	EE1	EE2	EE3	SI1	SI2	SI3	FC1	FC2	FC3	T1	T2	T3
Pre-usage questionnaire (x) Min = 1 (Strongly Agree) Max = 7 (Strongly Disagree)															
Valid N	485	485	485	485	485	485	485	485	485	485	485	485	485	485	485
Mean	2.80	2.84	2.66	2.44	2.09	2.47	3.46	3.55	3.59	2.28	2.26	2.24	2.52	2.40	2.58
Median	3.00	3.00	2.00	2.00	2.00	2.00	4.00	4.00	4.00	2.00	2.00	2.00	2.00	2.00	2.00
St. Dev	1.176	1.195	1.176	1.016	.942	.999	1.357	1.354	1.318	1.016	1.037	1.064	1.071	1.080	1.076
Variance	1.383	1.429	1.382	1.031	.887	.998	1.840	1.835	1.738	1.032	1.075	1.132	1.147	1.167	1.158
Mean Score x Construct	2.8			2.44			3.46			2.26			2.52		
Post-usage questionnaire (y) Min = 1 (Strongly Agree) Max = 7 (Strongly Disagree)															
Valid N	442	442	442	442	442	442	442	442	442	442	442	442	442	442	442
Mean	4.38	4.28	4.41	5.67	5.84	4.80	3.93	3.62	3.41	5.17	5.19	4.82	4.56	4.67	4.55
Median	4.00	4.00	5.00	6.00	6.00	5.00	4.00	4.00	4.00	6.00	6.00	5.00	5.00	5.00	5.00
St. Dev	1.536	1.548	1.527	1.342	1.241	1.435	1.658	1.598	1.596	1.522	1.508	1.503	1.607	1.569	1.579
Variance	2.360	2.395	2.333	1.800	1.541	2.060	2.748	2.554	2.547	2.315	2.275	2.259	2.583	2.461	2.493
Mean Score x Construct	4.38			5.67			3.93			5.17			4.56		
Pre-post Usage Reliability															
Cronbach α															
Pre-Post Usage	.866			.805			.921			.861			.913		
Composite Reliability															
pre-post usage	.632			.602			.900			.736			.431		
Overall Composite Reliability							.977								

consistent with the age profile of students enrolled in the courses and the age profile of those who accepted. In contrast to gender, there are no significant differences. More than 50% of students who replied to both the pre- and post-usage questionnaire were between 21 and 35 years old (concretely, 54.22% in the Faculty of Computer Science, Multimedia and Telecommunication and 61.95% in the Faculty of Economics and Business).

3.5. Data analysis: structural equation modelling

This study used SEM to analyse the relationship between the pre-usage and post-usage stages according to the UTAUT scale. SEM, widely used in social and behavioural research, provides the possibility of fitting a theoretical model and evaluating its fit through empirical data (Tarka, 2018). This approach was deemed appropriate to test our assumptions of change over time (disconfirmation) in the students' acceptance of innovative technologies such as EWS. Moreover, the literature on SEM highlights the need for adopting different approaches according to the type of study, the sample's normality and size. In our case covariance-based SEM was used according to the recommendation in Hair, Ringle, and Sarstedt (2011, p. 144), as preferred for procedures in which the goal is theory testing, theory confirmation, or comparison of alternative theories. Finally, according to the most frequent approaches in UTAUT and our own theoretical and modelling approach, we used reflective measures for the first and second-order constructs in our model. A reflective latent construct is based, but not exclusively, on the indicators. The latter indeed can be interchangeable, and removal has no implications for the latent constructs. Therefore, the reflective approach strives to maximise overlaps between basic indicators (statements) supported by the construct, which is the driver of the statements (Diamantopoulos & Siguaw, 2006).

Our modified UTAUT scale was based on five latent variables: PU, EE, SI, FC, and T. Said variables are not directly measured but yielded from the relationships and explanatory power of the direct variables/items in the UTAUT questionnaire. SEM analyses and interprets the reliability of (1) the measurement model and (2) the structural model. The structural model incorporates a linear specification (path) reflecting the dependencies between constructs (latent variables) and directly measured variables (items in the questionnaire). All the analyses were conducted with SEM in R 3.5, using the lavaan package for SEM and other complementary packages for subsidiary analysis (data polishing, re-shaping and descriptive statistics).

As for the first step (measurement model), the dataset was prepared to perform SEM. The missed values along the analysis and the outliers were also detected and cancelled using the Mahalanobis distance test for multivariate analysis for robust estimates (Olkin & Sampson, 2001). The data were not rescaled since the Likert scale provided stable parameters. To assess each of the scales' distributional properties, descriptive statistics, as well as kurtosis and skewness, were adopted.

The reliability was analysed through the Cronbach Alpha and Composite Reliability followed by a scale validation based on Confirmatory Factor Analysis (CFA). The analysis was performed considering each latent variable, the specific item loadings, the t-value and the Average Variance Extracted (AVE) for each construct. As a complementary step, not requested in the SEM procedure but aimed at understanding the change effect, the student's t-test was applied to the mean of the theoretical UTAUT scales.

As for the second step (path analysis), the structural equation was run over a covariance matrix. The following model fit indicators were used: X2/df, the root mean square error of approximation (RMSEA), the Tucker–Lewis index (TLI), and the comparative fit index (CFI). As for the measures of adequate fit, the cut-off values for the different indicators suggest that RMSEA should be < 0.06, CFI>0.90, TLI>0.90, and X2/df < 2 (Byrne, 2013). All the models used in our study satisfied the aforementioned conditions.

4. Results

The descriptive statistics supported the assumption of normal distributions. For the pre-usage questionnaire, the asymmetry values oscillated between a minimum of 0.317 for the SI3 scale and 1.209 for the FC2; and the kurtosis observed was 0.382 (SI3, min) and 2.495 (FC2, max). In the case of the post-usage questionnaire, the asymmetry values were −0.02 (SI3, min) and −1.33 (EE2, max); and the kurtosis oscillated between 0.02 (FC3, min) and 1.52 (EE2, max). The acceptable values to test normality are for indicators −2 and +2, with some tolerance for positive skewness in the cases of self-reported measures (Gravetter, 2011). Table 2 introduces the descriptive statistics considering the mean scores and standard deviations.

Table 3
Measurement model.

Model Latent		AVE	Cross Correlations											
Variables			PUx	EEx	SIx	FCx	Tx	xAll	PUy	EEy	SIy	FCy	Ty	yAll
Pre-Usage	PUx	.686	1											
	EEx	.557	.663	1										
	SIx	.805	.451	.404	1									
	FCx	.687	.647	.579	.394	1								
	Tx	.785	.830	.742	.505	.724	1							
	xAll		.861	.770	.524	.751	.964	1						
Post-Usage	PUy	.890	-.416	-.373	-.254	-.363	-.466	-.484	1					
	EEy	.706	-.283	-.253	-.172	-.247	-.317	-.328	.584	1				
	SIy	.838	-.291	.,260	-.177	-.254	-.326	-.338	.601	.408	1			
	FCy	729	-.311	-.279	-.190	−272	-.349	-.362	.644	.437	.450	1		
	Ty	.869	-.433	-.387	-.264	-.378	-.485	-.503	.895	.607	.625	.669	1	
	yAll		-.449	-.402	-.273	−392	-.503	-.521	.928	.630	.648	.694	.964	1

The Cronbach Alpha and the Composite Reliability were also measured the joint pre-post usage stages adopted in the model to accomplish the reliability analysis. As it can be observed, the Cronbach Alpha values yielded appropriate to excellent levels (>0.85, Vaske, Beaman, & Sponarski, 2017). As for the CR, administrating the scale in two different moments had a relevant impact, with scales performing slightly low (Trust, 0.431), but all the rest of the latent constructs were above the threshold level of 0.60 (PU, EE, SI, FC). Moreover, the overall CR was very good (Fornell & Larcker, 1981).

Table 3 provides the AVE and cross-correlation for the variables included in the model, generally supporting the assumption of convergent validity. As it is possible to see, AVE values are 0.5 or higher, which indicates a sufficient degree of convergent validity, meaning that the latent variable explains more than half of its indicators' variance. Discriminant validity is also good for the latent variables of the SIx, FCx and all the post-usage stage since the AVE was higher than the specific loadings.

As an additional analysis, given the pre-post usage comparison, the repeated measures student's t-test was adopted. The scales PU, EE, FC and T, the differences between the pre- and post-usage stages were significant, showing the disconfirmation effect, as shown in Table 4.

Overall, the students disagreed with the usefulness (PU) of the EWS. Moreover, they found the effort (EE) was considerably higher than expected, and the facilitating conditions (FC) were not enough to cover the EWS usage. Finally, their trust in the tool decreased (T). Nonetheless, it was interesting to find that the social influence (SI) connected to the usage of the tool did not change over time. From the beginning, the students were indifferent (3.46, near to "neither agree nor disagree") to the interest of peers or influential people using the EWS. According to the *t*-test, the small difference in the pre-post usage measurement (0.47) did not support the hypothesis of relevant change over time or relevant interest in external social influence when adopting the EWS. These results alone could be considered negative, but the modelling was applied to explore the relationship between pre-post usage acceptance in depth.

The initial model also displayed the following fit values: RMSEA = .075 (lower 90% CI = 0.07, upper 90% CI = 0.08), CFI = 0.94, TLI = 0.916), all values over the cut-off criterion. The Chi-square test (df = 435) yielded a significant p-value = 0, requiring correction. However, it is commonly accepted if the other fit measures are good and the p-value is not excessively small. A correction of the model was elaborated by exploring the Modification Indexes (MI). In fact, the co-variation between PU2(x) and EE3(x) was higher than expected (with a MI of 138.336). Also, the EE1(x) and the EE2(x) required attention (with a MI of 130.022). The model was tested, correcting those values. Moreover, the covariances mentioned above also had relevant theoretical explanations. The PU has been long related in the literature with the expected effort, in an indirect relationship: the higher the usefulness as perceived by the user, the lower the expected effort in its usage (Scherer & Teo, 2019). Therefore, the high covariance could be expected as systematic rather than error and the items were not removed. The case of EE1(x) and EE2(x) may derive from the item characteristics (very similar). Being at the pre-usage stage, the users might not be able to discriminate the content accurately. In the post-usage questionnaire, the PU2(y) and EE3(y) confirm the covariate effect and the EE1(y) and EE2(y) change. After removing this last pair from the model, the RMSEA, CFI, TLI and Chi-square did not improve in this second iteration. Overall, the model was deemed to have good convergent validity, reliability and discriminant validity. Consequently, constructs developed by this initial measurement were applied to test the research model.

Table 5 introduces model loadings and regression values. Factor loading is the correlation coefficient for the variable under analysis and the model's upper construct. Factor loading shows the variance explained by the variable on that particular factor. In the SEM approach, as a rule of thumb, 0.6–0.7 or higher factor loading shows that the variance extracted from a variable is sufficient. As for the R2, which measures the proposed model's fitness of the observed data in the context of regression analysis, a good cut-off value is > 0.40, with some tolerance for unexplored research areas (Hooper, Coughlan, & Mullen, 2008). The UTAUT model has been extensively investigated; therefore, we kept this (highest parameter) as a reference for the latent variables connected to acceptance (H1 and H2), with some tolerance for the disconfirmation effect (H3). In our model, both the factor loading and the R2 satisfied the criteria mentioned earlier. The only case in which the factor loading was lower for the traditional UTAUT model and only explained the 27.5% variance was the pre-usage social influence. If we consider that the pre-usage analysis was based on an abstract idea of what the EWS could be, it is possible to understand such an effect. The students, who are generally self-regulated adults, did not consider the influence of others to integrate the EWS into their academic activity. Therefore, it was a less relevant element in accepting the technology. However, the estimate resulted significant, and the hypothesis of social influence as part of the technology acceptance was not rejected.

Fig. 4 shows the results of the SEM paths testing. The relevant standardised loadings are also represented both for the direct and the latent variables.

5. Discussion

Except for the social influence in the pre-usage stage, all the constructs (PU, EE, FC, T) strongly support the H1 and H2 relating to

Table 4
Effect of disconfirmation.

Effect of Disconfirmation: *t*-test of paired pre-post usage stages (adjusted p-values with Benjamini & Hochberg method) Signif. Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1					
Constructs	Perceived Usefulness	Expected Effort	Social Influence	Facilitating Conditions	Trust
t-test values df = 324	t = −14.111, adj. p-value = 2.937504e-37***	t = −33.536, adj. p-value = 2.153514e-107***	t = −1.8779 adj. p-value = 0.06129931	t = −28.932 adj. p-value = 8.275703e-92***	t = −18.78 adj. p-value = 9.353481e-54***

Table 5
Results for the structural model and hypothesis testing.

Path	β	Estimate	P (>|z|)	R^2	Hypothesis (confirmation)
PUx	.861	1.443	0.000	.741	H1a Yes
EEx	.770	1.031	0.000	.593	H1b Yes
SIx	.524	0.525	0.000	.275	H1c Yes
FCx	.751	0.971	0.000	.564	H1d Yes
Tx	.732	3.085	0.000	.929	H1e Yes
PUy	.928	2.484	0.000	.861	H2a Yes
EEy	.630	0.811	0.000	.397	H2b Yes
SIy	.648	0.851	0.000	.420	H2c Yes
FCy	.694	0.964	0.000	.482	H2d Yes
Ty	.964	3.640	0.000	.930	H2e Yes
Regression					
EWS.ACCEPTx ~ EWS.ACCEPTy	-.521	-.611	0.000	.272	H3 Yes

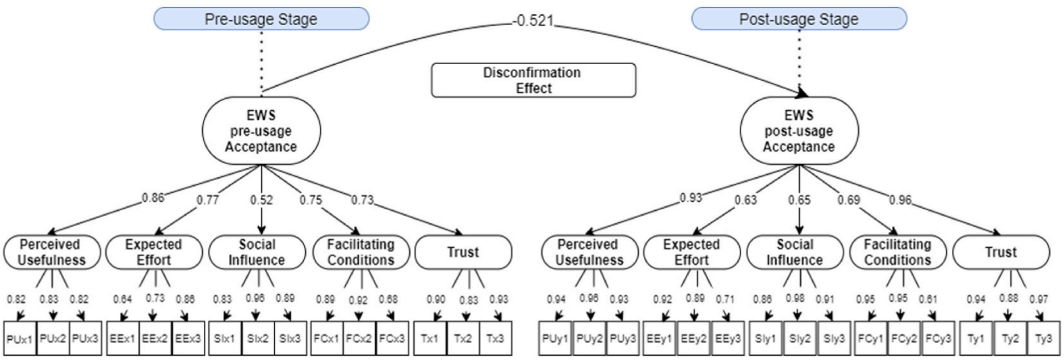

Fig. 4. Test model results: EWS technology acceptance and disconfirmation effect.

EWS acceptance components. In the pre-usage stage, the undergraduate students using the EWS consider it more acceptable as technology over the basis of the perceived usefulness (β = 0.861) as an internal condition predisposing them well to adopt it. Also very relevant are the expected effort (β = 0.77) and the facilitating conditions (β = 0.751) as constructs connected to more extrinsic conditions of usage (the cognitive and operational requirements connected to technology usage, and the availability of support when problems in usage arise). The students' level of trust (β = 0.732) as internal is not less relevant in an initial stage, pointing out a particular enthusiasm connected to advanced technology integration in their academic life. However, this item must be considered cautiously given the CR values. Finally, the lowest level was reached by the social influence (SI) at the limit of the cut-off value of 0.6 (β = 0.524). Such a value could be explained by the students' characteristics at the UOC. Most of them are working students and adults, and there is little room for close interactions in a fully online university. Also, the UOC pedagogical approach is mainly based on asynchronous activities. Therefore, the low SI value related the perception by such adult students of independence relating the other

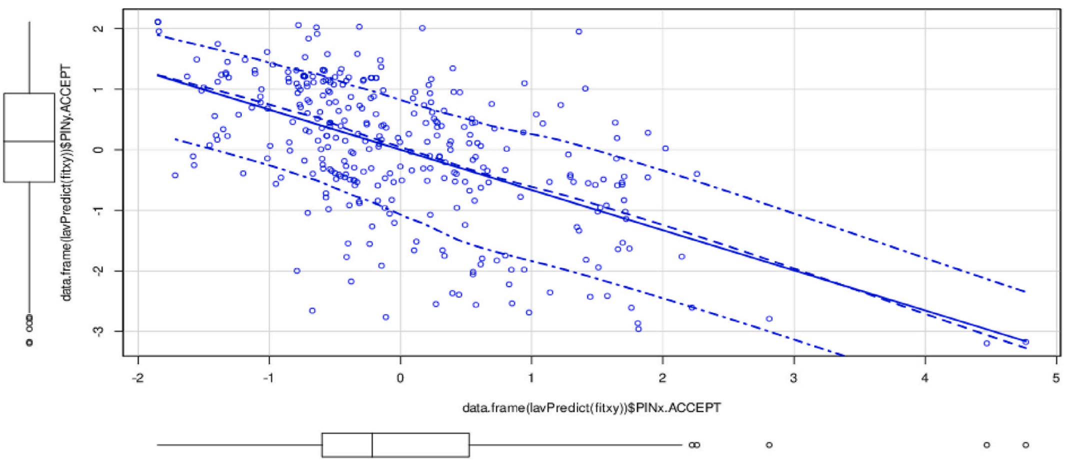

Fig. 5. Scatterplot showing the disconfirmation effect over students' expectancies.

classmates to accept and use the EWS.

In the post-usage stage, there is a disconfirmation effect between the overall acceptance of EWS in the pre- and post-usage stages. Hence, H3 was confirmed by the significant regression coefficient ($\beta = -0.521$). 27.2% of the model variance was determined by this relationship between the overall EWS acceptance in the pre- and the post-usage stages. The negative relationship also uncovers the phenomenon of disconfirmed high expectations. It appears that when the students start the experience with high levels of perceived usefulness and trust, the post-usage experience shows lower technology acceptance levels, entailing disagreement with the usefulness and the facilitating conditions. More importantly, the levels of trust in the EWS decrease in a consistent pattern ($\beta = .731$ and $\beta = 0.964$). The expected effort, which the students do not consider relevant in the initial pre-usage stage, also shows a negative pattern in the post-usage stage. There is disagreement with the ease of use (perceiving higher effort). However, there is more unexplained variability for this construct, and the answers appear to be more diversified in the second stage ($\beta = 0.77$ and $\beta = 0.63$).

Nonetheless, the negative relationship also highlights that there is a group of students whose perceptions and beliefs encompass lower expectations at the initial stage (pre-usage). This group also tends to improve their beliefs and expectations in the post-usage stage, supporting the disconfirmation hypothesis. The interesting effect of disconfirmation is also represented in the scatterplot graph Fig. 5.

Our EWS, designed as an evidence-based system for the students to self-regulate their learning or ask for help if needed, requires further intervention to be more integrated into the pedagogical activity. Students' perceptions, as well as teachers training, become a cornerstone to use AI in education. Our focus on user acceptance is highly relevant, given all the debate around the ethical use of learning analytics (Selwyn & Gašević, 2020; Willis, Slade, & Prinsloo, 2016). Implementation of EWS along the teaching and learning workflows should be considered a further opportunity to reflect on the impact of technological innovation on the quality of education. Usage data and analysis of the usage context are essential to developing IT applications that are likely to improve educational practice (Rose, 2019).

Another relevant issue to comment on is the divergence between the final low techno-pedagogical innovation acceptance and the students' actual performance. The EWS acceptance is lower than expected, probably because our EWS did not allow much student intervention. Despite this, it seems it might have had a positive impact on students' performance by comparing the performance between the students who consented and did not consent to participate in the study and the performance with students from the previous semester. We used the unpaired two-sample Wilcoxon test due to the non-normal distribution of the final mark. Students who did not deliver any assessment activity have been removed because they did not start the course, showing a low level of engagement. In each students' group comparison, the null hypothesis was that the median mark was lower in students who consented to participate in the study. Results are provided in Table 6. As observed, for the semester where the study took place, the performance was significantly better (i.e., we can refute the null hypothesis) in the group of students who consented to participate in the study (except in one of the four courses). Also, students who participated had better performance when compared with students who enrolled in the courses in the previous semester. Despite this, we cannot forget the fact that participation was voluntary. Students who tend to participate in this type of study are usually the most engaged and generally have better performance. Finally, the study coincided with the COVID pandemic. The strict lockdown we suffered, combined with a potential decrease in the students' professional and social activity, could have meant more time devoted to academic tasks, despite the widespread anxiety and concern. The performance of students who answered the pre- and post-usage questionnaires was not computed due to the restrictions imposed by the UOC Ethics Committee.

Overall, our findings answered the initially posed research question *When using an EWS, how does the acceptance level of learners change over time?* According to our model, based on our definition of EWS acceptance and the UTAUT survey measurements, the students change their acceptance response over time and in relation to their initial beliefs and expectations.

Besides, the theoretical and empirical elements considered before highlighted the complexities of understanding and measuring AI technological acceptance. While AI might generate high expectations, its role and integration within the educational practice (in particular) and human activity (in general) might be over-estimated. On the other hand, AI might have positive effects that are not perceptible for the students, whose emotional and motivational focus might be oriented towards teachers' presence.

6. Conclusions

HE institutions are currently devoting efforts to adopting technology to expedite the move to blended or online learning. However, even if institutions have been analysing the most promising technology to enhance learning, they sometimes leave behind some essential aspects where education and technology relay. This paper describes the analysis of students' acceptance of an EWS. Even though AI is a trendy topic in education, expectations about technology in real settings should be carefully analysed. Innovative technologies might generate unreal expectations when supporting online learning. Overall, the lack of adequate knowledge about AI technologies generates overly enthusiastic or reluctant reactions and is not adjusted to the specific support the AI might provide. For that reason, students' perceptions when using technology can shed light on these aspects so that institutions can be more effective.

Our findings have both theoretical and managerial implications concerning pedagogical practice. From a theoretical perspective, our findings reveal a disconfirmation effect on the acceptance of our EWS. When students had high expectations about technology, the post-usage experience showed lower levels of technology acceptance. Students might show different unreal expectations relating to the support provided by AI in their academic activity. Furthermore, our study analysed and modelled the students' acceptance of AI tools supporting their learning in HE through a longitudinal pattern. The importance of this focus was deemed twofold. On the one hand, exploring models that analyse longitudinal patterns of behavioural change relating to advanced technologies represent a source of societal change. On the other hand, to understand such patterns in the specific case of HE.

Consequently, from a managerial perspective, apart from adjusting and improving AI tool design continuously, teachers should also

Table 6
Results of the descriptive statistics and the unpaired two-sample Wilcoxon test on final performance.

	Computer Science, Multimedia and Telecommunication						Economics and Business					
	Computer Fundamentals			Databases			Markets and Behaviour			Introduction to Enterprise		
	Cons.	Not Cons.	Prev. Sem.	Cons.	Not Cons.	Prev. Sem.	Cons.	Not Cons.	Prev. Sem.	Cons.	Not Cons.	Prev. Sem.
No. Students	240	126	610	47	66	199	376	262	764	176	426	952
No. Engaged Students	165	80	544	45	65	194	357	210	544	169	345	855
Median	7	0	2	7.30	6.90	6.20	7.60	7.10	7.30	7.90	7.50	6.40
Mean	5.48	3.18	3.36	6.85	5.93	4.64	7.04	5.82	6.07	6.84	6.48	4.75
St. Dev	3.96	3.77	3.78	2.63	3.43	3.54	2.94	3.22	3.13	2.88	2.85	3.52
Min	0	0	0	0	0	0	0	0	0	0	0	0
Max	10	9.9	10	10	9.8	10	10	9.7	10	9.8	10	10
Results of the unpaired two-sample Wilcoxon test on final mark distribution (p-value)												
Consent		4.4e-06****	1.8e-09****		ns	5.1e-05****		2.0e-06****	2.2e-06****		0.0048**	2.6e-16****

note that the students might not be fully prepared for the enhanced AI tools' potential, especially without appropriate training. Therefore, it appears relevant to introduce AI technologies via phases of technological familiarisation.

The research's weaknesses relate to the convenience sample. Our intervention in the "ecological settings" of university courses prevented us from measuring and controlling variables such as the specific students' pre-post performance. Moreover, being only a quantitative study, we could not dig into the students' mindsets, beliefs, and motivations moderating their acceptance and confirmation/disconfirmation moment.

As remarks for future research and pedagogical practice, multidimensional analyses of a re-engineered version of the EWS rooted in actual usage are a model for future application development in research and practice. They may include considering interface design, the dashboard elements, integrating the teacher's feedback, and the social context for usage. Similarly, further studies could integrate a conceptual explanation on EWS informing the pre-usage moment to measure acceptance by eliminating the biased AI beliefs. Moreover, the EWS design requires qualitative approaches to understand the frustrations or motivations to interact with this type of system. Nonetheless, the aspects connected to data ethics and privacy could be explored to understand whether the students appreciate or fear their data usage, as part of the EWS user experience, amongst other AI tools potentially included in virtual classrooms.

Credit author statement

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Appendix A. Supplementary data

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