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The role of contextual and individual factors in successful e-learning experiences during and after the pandemic – a two-year study

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Abstract

The main aim of this study is to examine university students' satisfaction with remote learning, analysing their socio-demographic and personal factors, the perception of online interactivity and of the online means used by academics considering two important moments: one academic year from the pandemic period (2020–2021) and one from the post-pandemic period (2022–2023). The sample included 1493 university students in a cross-sectional correlation research design. We found significant direct effects of techno-creators and techno-inhibitors on satisfaction, and of e-learning use on satisfaction. Technostress inhibitors have significant positive effects on e-learning use, learning engagement and negative effects on technostress creators. The relationship between technostress creators and satisfaction is partially mediated by learning engagement and e-learning use. Uncertainty has mediated effects on e-learning satisfaction. The results show that students expected almost all the features of the platforms to be used more in 2022–2023, when classes became preponderantly face-to-face. The results are slightly different during the two years of the analysis.

Keywords Personal factors · Technological factors · Learning engagement · Student satisfaction · Technostress

Introduction

Prior to 2020, e-learning was primarily used as a supplemental tool for distance education or to complement traditional teaching. With the onset of the pandemic, remote learning became a compulsory method of education where teachers and students

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relied on online platforms, email, television, and radio to continue the learning process. The pandemic has forced educational institutions to extend the online or hybrid/blended learning for one or two academic years, and the shift to this online education brought a high level of stress among both students and teachers, mostly at the beginning of the pandemic. In this period, universities faced many challenges in adapting to the teaching-learning process in the online environment (Bruggeman et al., 2022).

Although most students frequently use technology today, their familiarity with technology in a learning environment is unequal for different groups (UNESCO, 2020a). While using online learning, some students are less confident in their abilities, feel more stressed, depressed, and lonely compared to face-to-face learning (Elmer et al., 2020). At the same time, the sudden shift to online learning, combined with the presence of health danger stimuli in the social context, has led to increased uncertainty, anxiety, and worry among students (WorldBank, 2020, p. 19).

Given the settings of contextual (Dwidienawati et al., 2020) and individual factors (She et al., 2021) related to e-learning, understanding the factors that contribute to successful e-learning experiences is critical. Previous literature has analysed the contextual and individual factors of learning when online learning was just an alternative to face-to-face learning. Our study analyses the opposition between the online environment in a period when it was the only learning environment, mandatory for students and teachers, in the first year of the pandemic, and blended learning in the second year. In addition, during the lockdown period, online learning was different from previous historical stages because it took place in a context of threatening and uncertain background that could increase students' level of anxiety or decrease their self-efficacy.

Since this context was maintained for two years, it is important to see if the students' perceptions of e-learning and its use have changed, our study being one of the few comparative studies in this respect. If the academic year 2019–2020 required students a great effort to adapt to a completely new context, in the next year the use of applications was probably already accepted and integrated in learning.

Our study adopted the personality-situation interactionist approach (Kuper et al., 2022), examining the learning experience as a response to the connection between students' characteristics and the learning situation marked by the mandatory digitalization of learning. We analysed the satisfaction of the learning experience as a core variable and as a consequence of the connection between the learning situation and students' characteristics, such as techno self-efficacy, learning engagement, tolerance to uncertainty and perception of online teaching and interactivity, as well as socio-demographic factors. We chose the students' learning satisfaction because it mirrors their perception of the learning experience (Littlejohn et al., 2016) and is a measure of learner centred success (Rabin et al., 2020). Understanding the associations of online learning satisfaction becomes a major factor for better supporting students online, increasing learning performance and learning satisfaction itself.

Furthermore, while the pandemic may have ended and teaching and learning may have returned to the face-to-face context, digitalization has become a major trend in education, requiring more independent students, able of handle technology to succeed with their individual or collaborative work (Reyes-Millán et al., 2023), revealing at the same time the role of digital competencies for all the parties involved (de

Obesso et al., 2023). In this "new normal" after the pandemic, the teachers play the role of coordinating and facilitating the online learning process in a highly interactive environment (Mhlongo et al., 2023). Therefore, evaluating the sustainability of e-learning beyond the pandemic is crucial to anticipate changes and adapt to new contexts, in order to meet the expectations of both students and teachers.

The transition of the universities to the digital world has shown the relevance of the digital competencies for all the parties involved (de Obesso et al., 2023). To improve learning performance and satisfaction, it is important to analyse their predictors during the pandemic, when the online learning environment was mandatory for some settings. The potential of digitalization in education was also emphasized in contrast to students' negative engagement with digital technology (Henderson et al., 2017; Selwyn, 2016). Hence, analysing the sustainability of e-learning after the pandemic is a significant issue. In this new context, for a successful learning process, students must develop effective study habits which involve time management, organizational skills and strong motivation (Reyes-Millán et al., 2023). Learners also need to develop strong reading, writing and communication skills and constantly improve their technological abilities in using digital tools (Kumalasari, 2022).

We formulated the following research questions:

RQ1. How did students use the e-learning platform and how did they perceive its usage by their teachers in the first year of the pandemic and after the pandemic?

RQ2. How did students' personal characteristics related to online learning evolve: techno self-efficacy, learning engagement, tolerance to uncertainty, and the relationships between them, in the first year of the pandemic and after the pandemic?

RQ3. How was students' satisfaction influenced by techno stress (creators and inhibitors) and by their personal and socio-demographic characteristics in the first year of the pandemic and after the pandemic?

The current paper first describes the research context, then it develops the hypotheses in the context of theoretical frameworks. It further continues with materials and methods, the instruments that were used, and the results. A significant section is dedicated to the discussions, the study contributions, and the limitations.

Research context

The university where the research was conducted is a comprehensive public Romanian university with over 20,000 students and over 700 teachers, with full-time and distance learning programs. Situated in the southeastern region of Central Europe, the country is recognized for its low indulgence, high uncertainty avoidance, collectivism, and power distance (Hofstede et al., 2010).

The university has owned an e-learning platform (Moodle) for distance learning since 2007, also used in full-time education as a resource platform for materials available to students, but also for assessment or communication. The rapid transition to online education, considered difficult and complex (UNESCO, 2020), has been favoured by this state of affairs.

In Romania, the closing of the face-to-face courses took place in mid-March 2020, and, as an alternative way, the e-learning platform was chosen for all forms and levels of education in the university under consideration. The e-learning platform was upgraded with the installation of the open source BigBlueButton (BBB) video-conferencing system, which became the recommended means of conducting courses and seminars. Being a synchronous channel of communication, the video conference was considered to allow focus on learners' needs, stimulate engagement in learning, increase the acquisition of information (Mader & Ming, 2015) and favour interactive exchanges (Conboy et al., 2017). Professors and students were offered support information for using the video conferencing system and all the features of the e-learning platform via both electronic documents and video guides.

Before the pandemic, in many European countries there was a huge delay in education digitalization. One of the reasons was the common belief that technology-based learning represents a risk to the quality of education (Bacci et al., 2023). Because the COVID-19 pandemic forced the teaching–learning process to take place only in the online environment, the interest in studying the antecedents and results of this type of process has increased a lot all over the world. In Italy, for example, studies have shown that students' distance learning satisfaction depends on some observable university characteristics and on some students' socio-demographic characteristics (Bacci et al., 2023). Studies conducted in the US have revealed that the perceived curriculum, campus support, and self-efficacy positively influence student satisfaction (Hong et al., 2023). The impact of the recent health crisis on the education sector has also been studied in Romania. It was revealed that the students who face problems related to unsatisfactory internet access, insufficient time due to other familial issues or inadequate working space at home are more likely to be less effective in their online learning process (Roman & Plopeanu, 2021). Another study has shown a decline in learning outcomes from one discipline to another (seminar scores, exam results), but also that student satisfaction with online learning remains at a high level despite an increased risk of academic failure (Dragomir & Dumitru, 2023).

Theoretical framework and hypotheses

Previous studies on learning satisfaction belong to a historical period in which online learning was optional, being targeted especially towards adults and used only for a part of the teaching-learning activities (Bolliger, 2004). The online teaching-learning activity prior to 2020 was explored in a quasi-normal situation where uncertainty and anxiety were not socially widespread (Chen et al., 2020). Many results of the previous studies on learning satisfaction are often inconsistent regarding gender, age (Yu, 2022), specialization, the use of Web Video conferencing (WVC) in learning (Fatani, 2020), or some psychological characteristics of learners (Bruggeman et al., 2022; Fuchs, 2022).

To determine the relationships between e-learning satisfaction and contextual and personal factors in the online environment, we integrated the model of bioecological university students' engagement in online learning (Bond & Bedenlier, 2019) and the job demands-resources theory (Bakker & Demerouti, 2017). The model of bioecological university students' engagement in online learning adapts the bio-ecological model (Bronfenbrenner & Morris, 2006) and introduces the digitalization of the learning environment and its relationships with other elements, such as power, culture, and economics in the macrosystem level. The new model zooms on the classroom microsystem considering the interaction with peers, teachers, tasks, and the connections with technology (Bond & Bedenlier, 2019). The determinants of students' learning are internal factors, such as psychosocial factors (acceptance, Information & Communication Technology (ICT) skills, prior ICT experience, self-efficacy, self-regulation, personality, motivation, interest, wellbeing, identity) and external factors, such as the learning environment and technology factors (access to technology, usability, design, assessment) (Bond & Bedenlier, 2019).

The job demands-resources theory (Bakker & Demerouti, 2017) defines job demands as physical, psychological, social or organizational factors that require different costs. It can be transferred into the university context, i.e. like working, studying full-time demands a substantial time investment. Job resources concern the factors that reduce the costs and effects of job demands. High job resources lead to high engagement and performance, while job demands consume resources and may lead to health problems (Bakker & Demerouti, 2017). Similar to employees, students participate in structured and organized activities (Cilliers et al., 2018), and they apply specific competences to accomplish academic tasks (Pluut et al., 2015). In addition, their activities are goal-oriented and evaluated externally (Cilliers et al., 2018). The externally assessed quality of these activities may impact students' future career (Lesener et al., 2020). In our research, job/study demands are related to the stress of using information technology, while job/study resources are related to stress inhibitors and personal factors, such as technology self-efficacy, and learning engagement.

Using the two described theoretical backgrounds, we propose a research model that responds to the research questions, focused on the factors influencing the e-Learning satisfaction, in the first year of the pandemic and after the pandemic (Fig. 1). Because teaching and learning are a multi-determined activity, the exploration of the factors involved, and their effects, is more complex. Consequently, we chose the specific elements that suit the crisis (as Uncertainty), the digitalization of the learning environment (such as e-Learning Use, Technostress), personal factors (self-efficacy, engagement) and the institutional context of the research (e-Learning facilities provided by university). The model suggests that learning satisfaction is influenced by personal factors, students' socio-demographics, and their perception of technostress and the use of the e-learning platform. Among the investigated variables, there are also other relationships whose identification is challenging because they provide a pattern of connections, offering a more comprehensive picture of the learning satisfaction.

Based on the research questions and the proposed model, we formulated several hypotheses that will be contextualized within the specialized literature in the field.

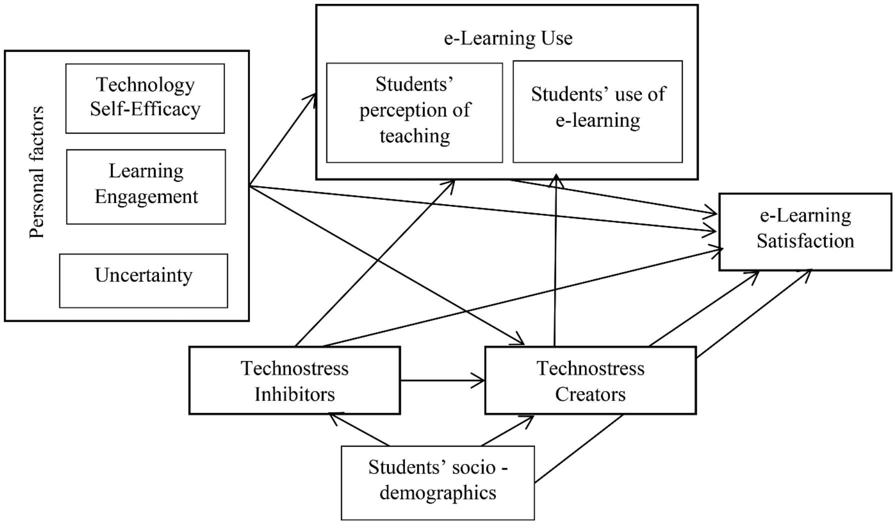

Fig. 1 Theoretical model of the research

Students' use of e-learning and their perception of teachers and teaching methods during the pandemic

The new e-learning environment during the period 2020–2021 impacted learning because some of the students had a low level of engagement and self-confidence in online classes, and they offered limited or no feedback to teachers e.g. (Al-Fraihat et al., 2020; Al-Jarf, 2020; Atmojo & Nugroho, 2021). At the beginning of the pandemic, in 2020, some students expressed negative opinion concerning e-learning, they accepted to use technology just as a complementary part in the education process, not as the alternative of the face-to-face education process, thus expecting changes related to higher education institution policies for returning to in-person classes (Manoharan et al., 2022). The strong influential factors on students' e-learning were the attractiveness of teaching methods, followed by the learning environment (Zhang et al., 2021) and teachers' technical competences (Thistoll & Yates, 2016). For teachers, there was a challenge in learning to adapt to students' needs and they realized that much effort needed to be done for continuing the teaching process (Marek et al., 2021). This situation led to an increased level of psychological pressure for them (Li & Yu, 2022).

After the pandemic, students have become more accustomed to e-learning, which could have positively impacted their engagement and attitudes towards it (Hanaysha et al., 2023). Moreover, teachers adapted their teaching methods and curricula in varying degrees to better suit e-learning, which could have positively impacted student engagement. Finally, teachers' digital competences have improved, as the lack of timely feedback or slow communication time frames from teachers before COVID could have diminished students' satisfaction with online learning (Pérez-Rivero et al., 2023). At the same time, students who perceive their interactions with teachers positively are more satisfied with online learning (Cidral et al., 2018; K.-S. Hong, 2002; Sun et al., 2008).

Therefore, the unprecedented changes introduced by the mandatory virtual learning led to the need to manage several challenges, including limited computer skills required for online learning. Also given the pandemic's prolonged duration, students and teachers may have adjusted to this new mode of education, leading to changes in e-learning use behaviour in the first year of pandemic, which were still present also after the pandemic (Pérez-Rivero et al., 2023). At the same time, the use of emergency e-learning programs increased students' resources to adapt to teaching methods which integrate technology (Murphy, 2020).

Based on the previous research and on our observation, the following hypotheses were formulated related to RQ1:

> H1.1.S (students) There are differences regarding the e-learning platform features used by students between 2020 and 2021 and 2022–2023.
> H1.1.T.(teachers) There are differences regarding students' perception of teachers' use of e-learning features between 2020 and 2021 and 2022–2023.
> H1.2. There are differences regarding students' technology self-efficacy, engagement, technostress, and the use of e-learning features between 2020 and 2021 and 2022–2023.

Intolerance of uncertainty

The intensity of emotions towards an uncertain, unknown situation and its negative consequences have been conceptualized as intolerance of uncertainty, defined as the individual's inability to manage the aversive reactions generated by the perceived absence of key and sufficient information, and is related to fear, anxiety, worry/concern (Carleton, 2016). Stress, anxiety and intolerance of uncertainty were correlated negatively with learning motivation and the frequency of distance learning attendance. The strength of the relationships between intolerance of uncertainty and distance learning motivation was significantly increased via anxiety (Göksu et al., 2021).

The Covid-19 pandemic has been an uncertain, threatening period in which some individuals experienced anxiety associated with high levels of drug and alcohol coping, suicidal ideation, and hopelessness (Lee et al., 2020). In this social context, remote teaching has put pressure on students' well-being and success (UNESCO, 2020). Thus, we assume that (RQ2):

> H2. Students' intolerance of uncertainty (1) was higher in the 2020–2021 academic year than in 2022–2023 and (2) negatively influenced students' satisfaction.

E-Learning satisfaction and its association with learning engagement and technology self-efficacy

In optional online education, learning satisfaction is the student's perception of a good course experience (Bolliger, 2004) or the user's overall emotional experience when using the system (Graetz, 2006). Satisfaction with online courses is influenced by instructor, interactivity, and technology (Al-Fraihat et al., 2020; Bolliger, 2004), by the difference between the perceived performance and expectations (Bhattacherjee, 2001), the perceived ease of use and prior experience with online courses (Bond & Bedenlier, 2019; Joo et al., 2016). The students are more satisfied when they interact with their teachers during the remote assessments (Senel & Senel, 2021).

The results regarding the use of web-based video conferencing (WVC) in learning are divergent: students' satisfaction increases due to the attachment to the class/peer group and the sense of community created by online discussions, thus diminishing the feeling of isolation (Dawson, 2006), but other studies cite WVC as a barrier to the interaction with the instructor (Doggett, 2008; Trespalacios & Rand, 2015). The satisfaction modifies the attitude towards the online environment, which can increase students' engagement and retention (Roddy et al., 2017), and influences the user's willingness to continue using this environment (Bhattacherjee, 2001; Chen et al., 2020; Joo et al., 2016).

In certain countries, studies have found that the primary factor affecting satisfaction with online learning during the pandemic is the availability of the platform. These studies, such as the one conducted in China (Chen et al., 2020), highlight the significance of technology and mobile devices in this regard. During this period, research has also indicated that a considerable percentage of students (82%) have expressed high levels of satisfaction with the web-based video conferencing method. They have reported a clear understanding of the subjects being taught, acknowledged the cognitive challenges of their online sessions, and appreciated the teachers' encouragement to actively participate (Fatani, 2020).

Students' learning engagement

The engagement in learning can be approached from the perspective of the energy and effort driven by the student in learning (Gunuc et al., 2022), observable at the behavioural, cognitive and affective level (Boekaerts, 2016). Other studies have addressed engagement as a positive work-related mental state, including vigour, dedication, and absorption (Schaufeli & Bakker, 2004).

Learning engagement is positively related to academic performance (Hanaysha et al., 2023) and mediates the relationship between computer self-efficacy and learning performance (Chen, 2017a,b). A positive relationship between students' engagement and the use of technology has been found (Rashid & Asghar, 2016; Webb et al., 2017), mostly in the STEM (science, technology, engineering, and math) and medicine fields (Howard et al., 2016). In opposition, other studies suggest that technology can also trigger students' disengagement with learning, while technology self-efficacy has a negative effect on online learning engagement during the Covid-19 pandemic (Heo et al., 2021). Therefore, more evidence is needed to understand the role of engagement in online learning.

Students' technology self-efficacy

Self-efficacy is the individual's belief/judgement about his/her ability to mobilize cognitive resources, motivation, and control the events to perform any task (Bandura, 1986). It can vary across different domains and has the role of a focal determinant of behaviour, both by its direct effects and by its influence on the other determinants (Bandura, 2012). Bandura's work suggests that people's perceived self-efficacy influences their choices and behaviours. If individuals feel they lack the necessary coping skills for challenging situations, they tend to avoid them. Conversely, if they believe their coping skills are sufficient, they are more likely to engage in those situations. Anticipating success, self-efficacy also affects individuals' coping efforts once they have started. Individuals who perceive themselves as capable are more likely to succeed in their tasks.

There is significant positive relationship between academic self-efficacy, students' engagement and online learning satisfaction (Linnenbrink & Pintrich, 2003; Chen, 2017a,b; She et al., 2021). Computer and internet self-efficacy have been equal for female and male, younger and older university students over the last decade, (e.g., Maican & Cocoradă, 2017), but they have been different at students enrolled in Arts and Science domains, in favour of Science (Abdullah & Mustafa, 2019). Self-efficacy with online courses is associated with a preference for the online learning environment, being a determinant of students' learning satisfaction (Heo et al., 2021). In the current study, only technology self-efficacy is used, which is different from academic self-efficacy.

Based on mixed results, the following hypotheses were proposed, based on RQ2:

> H3. The students' use of the e-learning platform (1), learning engagement (2), and technology self-efficacy (3) have both direct and indirect positive effects on satisfaction.

Technostress and its effects on e-learning

In higher education, studies highlight the positive and negative impact of ICT on students' academic productivity (Upadhyaya & Vrinda, 2020), increase in performance, and satisfaction (Schlachter et al., 2017). Technostress was defined as a disease of adaptation expressed by the defective physiological and psychological reactions generated by the interaction with new technologies (Craig, 1986). ICT stressors, related to the academic environment, have been grouped in techno-overload, techno-invasion, techno-complexity, techno-insecurity and techno-uncertainty, all called technostress creators (Ragu-Nathan et al., 2008). Recent studies have found that job/study demands are a direct predictor, while job/study resources and personal resources are an indirect predictor of techno-strain (Kim & Wang, 2018). Studies from the previous decade relate technostress to age (people older than 22 years report higher stress), the level of experience in ICT (those with less than 10 years report higher stress) and gender, women being more stressed (Salanova et al., 2013), including digital natives (Upadhyaya & Vrinda, 2020). Anxiety towards the computer and the internet is lower in the case of males, younger students, and students in the Science domain. The students in Humanities are more anxious and have more unfavourable attitudes towards the internet than those in Science, confirming the positive impact of skills and interests over anxiety (Maican & Cocoradă, 2017). The stress level with university students is negatively related to self-efficacy (Navarro-Mateu et al., 2020).

Technostress inhibitors seen as job/study resources, as literacy facilitation, technical support provision, and involvement facilitation, diminish technostress and its negative consequences (Fuglseth & Sørebø, 2014; Ragu-Nathan et al., 2008). Technostress inhibitors are expected to increase academics' satisfaction in e-learning systems and indirectly affect the disposition to extend the use of ICT (Fuglseth & Sørebø, 2014).

Furthermore, all these studies analysed the relationships of technostress with other variables in an environment where online learning was optional. We want to verify these relationships in a situation where online learning is mandatory, the only way to learn.

Based on these findings, the following hypotheses were developed from the RQ3:

H4.1. Technostress creators have negative effects on (1) students' satisfaction, (2) learning engagement, and (3) e-learning use.
H4.2. Technostress inhibitors have positive effects on (1) students' satisfaction, (2) learning engagement and (3) e-learning use, and (4) negative effects on technostress creators.

Impact of socio-demographic factors in online learning

Studies on the socio-demographic factors and attitudes of students in online learning are inconsistent: some argue that older students spend longer time in online activities (Dabbagh, 2007; Lim et al., 2006; Wojciechowski & Palmer, 2005); other studies show that younger university learners (20–29 years old) are more satisfied with the quality of online courses, have higher scores on knowledge tests, while older adult students tend to have weaker technical skills (e.g., Lim et al., 2006). However, significant direct, but weak correlations were identified between age and online course satisfaction (Ke & Kwak, 2013). Participants who have more experience in using computers are more satisfied with the course (K.-S. Hong, 2002). Male students use technology more and prefer other activities compared to female students (Cazan et al., 2016). In contrast, other studies showed that users' characteristic factors, such as age, gender (K.-S. Hong, 2002) and education level do not directly influence their satisfaction (Chen et al., 2020).

The students who have technical and mathematical expertise in using information technology (e.g. STEM students) have favourable attitudes about computers and the internet and low anxiety, while students from SSHA have higher uncertainty in using the computer and the internet and lower confidence in their ability (Cazan et al., 2016). In the context of these inconsistent findings, the last hypothesis, related to *RQ3* is the following:

H5. Predictors of e-learning satisfaction acted differently in 2020–2021 and 2022–2023 depending on socio-demographic characteristics (gender, age, educational level, field of study).

Materials and methods

The main objective was to describe and explain the influence of technostress creators and inhibitors, learning engagement, techno self-efficacy, uncertainty and use of the online platform on the students' satisfaction in the pandemic period (2020–2021) and after the pandemic (2022–2023). A quantitative, cross-sectional study which compares two subsamples, 2020–2021 and 2022–2023, was designed.

Procedure and participants

Data were collected using the open-source LimeSurvey application between May and July 2020 for the first part of the study, and between April and May 2023 for the second part. The participants were recruited via email using the institutional email addresses provided to each enrolled student. Two email messages were sent to all our university students, one in 2020 and one in 2023. The messages contained the text of the invitation to participate in our survey, as well as a link to an anonymous questionnaire. Two weeks after the initial emails were sent, a reminder was also sent to all the students. All students who took part in our study participated without financial or other compensations. The response rate for the full questionnaire was 3.4% in 2020, with a completion rate of 50.8%, and 4.5% in 2023, with a completion rate of 38.1%.

The sample consists of only fully completed answers and it includes 1493 university students, females (62.3%) and males (37.7%), in various study programmes (Table 1). The sample is a convenience one, self-selected. 46% participants are from STEM (sciences, technology, engineering, mathematics) domains, and 54% participants are from SSHA (social sciences, humanities, arts). In 2020, 46.3% participants were in their first year of study, at their first interaction with the university e-learning platform; in 2021, 41% were in their first year of study. It is possible that these 41% of participants had experiences with e-learning platforms in high school in the first year of the pandemic; the remaining 59% of the participants had interacted with the university e-learning platform in the previous year.

Table 1 Sample structure

Year	Females	Males	SSHA	STEM	TOTAL
2020-21	423	204	391	236	627
2022-23	507	359	414	452	866
TOTAL	930	563	805	688	1493

Note SSHA = social sciences, humanities, arts, STEM = science, technology, engineering, and math

In 2022–2023, the percentage of students who spent more than three hours studying online decreased and the percentage of those who devoted less than 3 h to this activity increased (Table 2).

The current study employed structural equation modelling (SEM). Partial least squares (PLS) SmartPLS 3.0 (Ringle et al., 2015) was used to analyse data. PLS-SEM has many advantages, including the relaxation of normal distributional assumptions inherent in the maximum likelihood method utilized by CB-SEM for model estimation. Furthermore, PLS-SEM exhibits a notable capacity to effectively estimate complex models even when confronted with limited sample sizes (Gefen et al., 2011; Hair et al., 2019; Shiau et al., 2019, 2020). In comparison to CB-SEM, PLS-SEM proves more advantageous for the current investigation, particularly in instances where the research objectives involve exploratory research for theory development, predictive analysis, complex structural models, inclusion of one or more formative constructs within the structural model, small sample sizes attributable to a limited population, non-normally distributed data, and the necessity for latent variable scores for subsequent analyses (Gefen et al., 2011; Hair et al., 2019; Khan et al., 2019; Shiau et al., 2019, 2020).

The hypotheses were tested with bootstrapping of 5000 resamples. To analyse the mediation effects, we used Preacher and Hayes (2004) recommendation, while the results interpretation was guided by Chin (2010). The analysis of VIF values for the assessment of multicollinearity showed VIF values lower than 2, suggesting that collinearity is not an issue.

The testing for bias was accomplished by using two versions of the Common Method Variance. We first tested the model using Harman's Single Factor Test, where we obtained 22.453% of the total variance. The second test was accomplished by using the method suggested by Kock (2015), using Variance Inflation Factors where all the VIF values were lower than the 3.3 suggested threshold. Based on the data from both tests, our model can be considered free of common method bias.

Instruments

The *tolerance to uncertainty* was measured with the Short Version of the Intolerance of Uncertainty Scale (Carleton et al., 2007). The scale measures reactions to uncertainty, ambiguous situations, and the future. The twelve items measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) can be grouped into two dimensions, Prospective anxiety (7 items, Cronbach's Alpha of

Table 2 Time spent on online activities

Time for online activities	Year 2022-23 (students' %)	Year 2020-21 (students' %)
Less than 1 h	5.9	2.7
1–2 h	16.1	13.9
23 h	24.5	16.6
3–4 h	16.5	22.3
More than 4 h	37.1	44.5

Note Chi^2 (4) = 31.39, sig < 0.001

0.79) and Inhibitory anxiety (7 items, Cronbach's Alpha of 0.84). Cronbach's Alpha for the entire scale was 0.88.

Technostress creators (TC) were measured using the 23-item Technostress scale (Tarafdar et al., 2015). It measures techno-overload (5 items, CA=0.90): e.g. *I am forced to change my work habits to adapt to new technologies*; Techno-invasion (4 items, CA=0.89): e.g. *I spend less time with my family due to this technology*); Techno- complexity (5 items, CA=0.88): e.g. *I often find it too complex for me to understand and use new technologies;* Techno-insecurity (5 items, CA=0.80): e.g. *I have to constantly update my skills to avoid being replaced;* and Techno-uncertainty (4 items, CA=0.83) e.g.: *There are constant changes in the computer software in our organization*. Cronbach alpha for the entire sample was 0.82.

Technostress inhibitors (TI) were measured using the technostress inhibitors scale (Ragu-Nathan et al., 2008). The scale conceptualizes technostress as being manifested in the three dimensions: Literacy facilitation (5 items, CA=0.80) e.g.: *Our organization provides end-user training before the introduction of new technology;* Technical support provision (4 items, CA=0.90) e.g. *The IT department in our organization is well staffed by knowledgeable individuals;* and Involvement facilitation (4 items, CA=0.75, e.g. *We are encouraged to try out new technologies*. Cronbach alpha for the entire sample was 0.89.

Technology self-efficacy (TSE) was measured using five items from the Technology self-efficacy scale (Liou & Kuo, 2014). The 5 items are rated on a 5-point Likert scale ranging from 1 (not at all characteristic of me) to 5 (entirely characteristic of me) and measures the belief in one's ability to successfully perform online tasks in educational settings. Example: *Whether the use of online technology is difficult or easy, I am sure that I can understand it*. Cronbach alpha for the entire sample was 0.91.

Positive *learning behaviour and learning-related state of fulfilment* (LE) was measured by means of the adapted *Utrecht (Learning) Engagement Scale* (Schaufeli et al., 2006) (CA=0.93). We used the 9-item scale that has a two-factor model containing a reduced Burnout factor and an expanded Engagement factor and it consists of 3 sub-scales, measuring Vigour (CA=0.91), Dedication (CA=0.85) and Absorption (CA=0.73).

E-learning satisfaction (SAT), a tool built for this research, consisting of 18 items, CA=0.93 for the entire scale. Examples: *If you think about learning methods through online platforms, you: can solve better the tasks proposed by the teacher/ work more easily collaboratively during class* or *Overall, how satisfied are you with your recent online teaching experience*?

The *Use of e-learning platforms* (E-learning) in learning activities was measured through 21 items on a five-point Likert scale, 1 (almost never) to 5 (almost all the time) and grouped, after exploratory factor analysis, in two scales: *Use of online features for learning* (9 items, and Cronbach's alpha coefficient (CA)=0.76) e.g., '*Solving and uploading assignments', 'Self- evaluation by solving the tasks received', 'Sharing materials with colleagues'*; *Student's Perception on the use of online features for teaching* (12 items, CA=0.82) e.g., '*Posting individual feedback for students.'*, '*Posting questions for student self-assessment', 'Monitoring individual student progress through continuous evaluations'*. The items for the two sub-scales are built mirroring the two situations (teaching and learning), and it was adapted from (Cazan & Maican, 2023). The entire scale has CA=0.86.

Results

Differences between 2020 and 2021 and 2022–2023 (H1, H2)

According to the data comprised in the following table, the online usage of the applications of the e-learning platform in 2022–2023 differ significantly compared to 2020–2021 concerning few features (Table 3). The biggest differences in the use of online platform features by students are related to the use of chat (more common in the second year of the pandemic), followed by participation in audio/video conferences and receiving feedback from teachers (more common in the first year of the pandemic), but the effect size is low in all variables.

The data in Table 4 show the significant differences regarding students' personal traits between 2020 and 2021 and 2022–2023, the uncertainty and technostress being higher in the first year of the pandemic, while Technology self-efficacy, E-learning use, and E-learning satisfaction are higher after the pandemic period.

Out of the respondents' socio-demographic characteristics (gender, age, cycle of study, field of study, year of study), only gender influences the average time spent on each activity during this period, according to the results of the Chi-Square test, applied to each of the characteristics (Table 5). In this case, females spent more time online in both years: median time spent online being 5 h (2020-21) / 3.5 (2022-23) vs. males 4 (2020-21) / 3 (2022-23).

Both in 2020–2021 and 2022–2023, students wanted teachers to use more frequently almost all applications provided by the e-learning platform (Table 6). Top three applications that students would have liked teachers to use more frequently are uploading course and seminar materials in extenso (4.62), solved application models (4.60), and assignments (4.54).

Testing the research model

The path model was estimated using Smart-PLS 3.0. Because the test for the overall model fit has been introduced only recently in PLS-SEM, the values presented in Table 6 should be interpreted with caution (Benitez et al., 2020; Hair et al., 2019). The SRMR was lower than the suggested threshold of 0.080, indicating a good model fit (Table 7), thus confirming and explaining student involvement by means of remote learning engagement and their usage of e-learning platforms. Students' satisfaction is predicted by their involvement in learning, use of e-learning features, self-efficacy, technostress inhibitors (positively) and technostress creators, as well as by their reaction to uncertainty (negatively).

In our study, the questionnaire for e-learning use for learning was adapted (mirrored) from the one designed for teaching, as validated in another study by (Cazan & Maican, 2023). In the current study, we wanted to see if the structure obtained for teachers is also maintained for students, e.g. (1) Teaching (in the previous study)

Table 3 Features of the online platform used by students

Year	SA	MU	A/ VC	CH	SAQ	SMP	FB	FO	STC
2022-23 M (SD)	4.38(0.83)	4.29(0.84)	4.02(1.03)	**3.88(**1.10)	3.56(1.25)	3.45(1.21)	3.25(1.30)	2.57(1.25)	2.51(1.19)
2020-21 M(SD)	4.44(0.84)	4.36(0.81)	**4.23(**1.09)	3.25(1.36)	3.60(1.27)	3.48(1.23)	**3.50**(1.33)	**2.70**(1.27)	2.41(1.19)
T	1.47	1.66	3.53	9.91	0.55	0.53	3.72	-1.9	1.68
Sig	0.14	0.09	<0.001	<0.001	0.57	0.59	<0.001	0.057	0.09
d Cohen	0.017	0.085	0.198	0.510	0.032	0.020	0.190	0.030	0.080

Note SA=Solved applications, MU=Materials uploaded by the teacher, A/VC=Audio/Video conferences, CH=Chat, SAQ=Self-assessment questions, SMP=Sharing materials with peers, FB=Feed-back, FO=Forum, STC=Student- teacher communication

The values in bold represente the values that are higher, only for the differences that are statistically significant vs. Perception by students of the use of online features for teaching and (2) Student Comprehension / Continuous assessment (previous study) vs. Use of online features for learning. The final “E-learning use” variable was considered a second-level formative construct that was built with two sub-dimensions (Use of online features for learning” and “Perception by students of the use of online features for teaching). The justification for creating a level 2 level was also based on the correlation (0.567, $p<.01$) obtained between the 2 dimensions. Given the good fit indices (Table 7), we opted for this model. The values of indicator loadings for reflective measures were all above 0.653, demonstrating adequate convergent validity for the measured constructs.

The composite reliability for each construct was at least 0.84 and showed acceptable levels of internal consistency reliability (Table 8).

For assessing discriminant validity ensuring that reflective constructs have the strongest relationships with their own indicators, we used the HeteroTrait-MonoTrait ratio of correlations. All the values were below the 0.90 suggested threshold, meaning that discriminant validity has been established between the reflective constructs (Table 9)

The constructs correlation matrix after the evaluation of the models between the two investigated years is presented in Table 10.

To test H3 and H4 hypotheses, we ran several mediation analyses, using technostress inhibitors, techno self-efficacy and uncertainty as antecedents, technostress creators, learning engagement and e-learning-use as mediators, and satisfaction as dependent variable (Fig. 2). The total variance explained varies between 2020 and 2021 and 2022–2023, being 0.627 and, respectively 0.638.

The results revealed that:

- the use of the e-learning platform, learning engagement, and technology self-efficacy have direct positive effects on satisfaction, validating the first part of H3;
- - technostress creators have significant direct and negative effects on satisfaction and learning engagement both in 2020–2021 and 2022–2023; they have negative significant effects on e-learning use only in 2022–2023, thus H4.1 is supported;
- - technostress inhibitors have significant direct positive effects on e-learning use, learning engagement, and negative effects on technostress creators (H4.2 - supported).

The analysis of the indirect effects showed various relationships between independent variables and e-learning satisfaction: the relationships between techno self-efficacy and satisfaction is partially mediated by students’ learning engagement, technostress creators, and e-learning use on multiple paths, both in 2020–2021 and 2022–2023 (Table 11a). Therefore, the presence of the indirect effects of techno self-efficacy on satisfaction (H3.3) is confirmed. The effect of techno self-efficacy remains positive, albeit significantly decreasing, through the inclusion in the chain of techno-creators and e-learning use.

Based on H4.1 and H4.2, another significant finding showed the indirect effect in the partial and serial mediations from technostress creators to satisfaction through e-learning use and learning engagement (both 2020–2021 and 2022–2023). Effects

Table 4 Differences between 2020-21 and 2022-23

Year	UNC	TSE	TC	TI	LE	ELU	SAT
2020-21 *M(SD)*	**3.4**(0.65)	3.87(0.82)	**2.91** (0.73)	**2.9** (0.74)	2.67 (0.84)	3.42 (0.61)	3.07(0.92)
2022-23 *M(SD)*	3.14(0.72)	**4.14** (0.7)	2.37 (0.71)	2.35(0.71)	**3.04** (0.97)	**3.5** (0.62)	**3.62**(0.90)
t	7.231	6.66	14.54	14.49	7.85	2.61	11.50
sig	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
d Cohen	0.38	0.35	0.75	0.75	0.41	0.13	0.60

Note UNC = Uncertainty, TSE = Technology self-efficacy, TC = Technostress creators, TI = Technostress inhibitors, LE = Learning engagement, ELU = E-learning use, SAT = E-learning satisfaction

The values in bold represente the values that are higher, only for the differences that are statistically significant

Table 5 Differences regarding students' socio-demographic characteristics with respect to the time dedicated to online activities

Characteristics	2020-21			2022-23		
	Chi^2	df	sig	Chi^2	df	sig
Gender	52.65	4	<0.001	22.91	4	<0.001
Age	23.51	20	0.264	27.35	20	0.126
Year of study	25.26	20	0.07	21.59	20	0.363
Level of study	22.16	8	0.005	10.07	8	0.260
Domain of study	23.47	20	0.266	21.70	20	0.357

from techno inhibitors to satisfaction are positive, being mediated through e-learning use and learning engagement, as well as technostress creators (Table 11b).

Direct effects of Uncertainty on students' satisfaction (H2.2) are not significant. However, there are indirect and negative effects partially mediated by technostress creators, learning engagement, and E-learning use at significant level and these effects are negative. Other mediations from Uncertainty to students' satisfaction are not significant (Tables 11c and 12).

To test H5, we ran several multi-group analyses (MGA) related to the years of the study (2020–2021 vs. 2022–2023). The sociodemographic characteristics used were gender (F/M compared between and across years) and study domains (STEM/SSHA compared between and across years), testing for significant differences between the groups. H5 is partially supported, some important differences between the groups being (Table 12):

- Technostress Creators have higher direct effects on Satisfaction in 2022–2023 comparted to 2020-21, but the total effects differences are not significant across the two compared periods;
- Learning engagement has higher effects on Satisfaction in 2022–2023 compared to 2020–2021 for female students and SSHA programs;
- Technostress inhibitors influence E-learning use, the effects being higher in 2020–2021 compared to 2022–2023 (females);
- Technostress creators and inhibitors impact e-learning use, more in the case of females than males;

Table 6 Comparison between students' perception of online platform features used by teachers versus students' expectations (H1.1.S, H1.1.T)

Online platform features used by teachers vs. Features expected to be used by teachers	Means in the two years		Statistics tests					
			Year (2020-21 vs. 2022-23)			Features used vs. Expected to be used (globally)		
	2020-21	2022-23	*F*	*sig*	*Eta²*	*F*	*sig*	*Eta²*
A/V Conferences	4.10	4.26	6.72	0.010	0.003	32.14	<0.001	0.006
	4.30	4.37						
PowerPoint presentations	3.70	4.23	93.7	<0.001	0.04	163.71	<0.001	0.03
	4.18	4.48						
Assignments	4.31	4.21	0.60	0.438	<0.001	43.13	<0.001	0.012
	4.38	4.54						
Course/ seminar in extenso	3.96	4.17	25.10	<0.001	0.01	257.82	<0.001	0.5
	4.44	4.62						
Chat	3.33	3.53	25.56	<0.001	0.12	285.82	<0.001	0.046
	3.78	4.09						
A/V Resources	2.84	3.38	64.46	<0.001	0.02	1131.31	<0.001	0.22
	4.24	4.43						
Solved applications	3.15	3.27	1.31	0.25	<0.001	1704.14	<0.001	0.336
	4.64	4.60						
Self-assessment questions	2.74	2.96	13.06	<0.001	0.004	839.27	<0.001	0.186
	3.92	4.04						
Feedback	3.01	2.92	5.77	0.016	0.002	1500.49	<0.001	0.270
	4.40	4.27						
Assessment throughout the course	2.75	2.89	2.44	0.118	<0.001	740.19	<0.001	0.165
	3.88	3.89						
Forum	3.09	2.88	0.22	0.636	<0.001	468.52	<0.001	0.08
	3.54	3.80						
Antiplagiarism software	2.43	2.81	26.98	<0.001	0.010	748.46	<0.001	0.149
	3.62	3.79						

Note first line presents the features of the online platform used by teachers, as perceived by students. Second line - platform features students expected teachers to use

Table 7 Model fit

Fit indices	2020-21	2022-23
SRMR	0.05	0.05
d ULS	2.78	2.99
d DG	0.82	0.85

- There were no differences concerning the level of study and age across the two years.
- Uncertainty has greater effects on learning engagement in 2022-23 compared to 2020-21 in the case of females, while it has greater impact in 2020-21 for SSHA programs.
- Technology self-efficacy has greater direct effects on e-learning engagement in 2022-23 for SSHA programs compared to 2020-21, but their total effects are not different.

Table 8 Composite reliability for each reflective investigated constructs

Investigated constructs	2020-21			2022-23		
	CA	CR	AVE	CA	CR	AVE
Uncertainty	0.84	0.88	0.52	0.88	0.90	0.58
Satisfaction	0.93	0.94	0.52	0.94	0.95	0.57
Techno self-efficacy	0.90	0.93	0.72	0.88	0.91	0.64
Technostress creators	0.93	0.94	0.50	0.93	0.94	0.49
Technostress inhibitors	0.89	0.91	0.54	0.90	0.92	0.57
Learning engagement	0.92	0.93	0.61	0.94	0.95	0.68

Note CA = Cronbach's Alpha, CR = Composite Reliability, AVE = Average Variance Extracted

Table 9 Heterotrait-monotrait ratios in 2020–2021 vs. 2022–2023

2020-21 / 2022-23	LE	SAT	TSE	TC	TI	UNC
Learning Engagement (LE)	1					
Satisfaction (SAT)	0.73/0.74					
Techno self-efficacy (TSE)	0.54/0.49	0.59/0.54				
Technostress creators (TC)	0.54/0.50	0.56/0.53	0.67/0.59			
Technostress inhibitors (TI)	0.52/0.52	0.49/0.45	0.36/0.33	0.36/0.33		
Uncertainty (UNC)	0.30/0.24	0.25/0.21	0.38/0.29	0.47/0.41	0.14/18	1

Note All the correlations are significant at $p < .001$

Discussion

In our study, most of the hypotheses were supported by data and some are only partially confirmed. The results showed that the frequency of using the features of the online platform decreased slightly during the academic year 2022–2023 compared to 2020–2021, while students expected that teachers use almost all the features provided by the e-learning platform more frequently in the second year.

Satisfaction was directly predicted by self-efficacy, techno creators, e-learning use, and learning engagement. The effects of learning engagement are similar for both years and it was a significant mediator on the relationship between technostress creators/inhibitors, e-learning use and satisfaction. The direct adverse effect of technostress creators remains negative, but significantly decreases through the mediation of learning use and learning engagement in both years of the research.

The e-learning use in two years – a student centred approach (RQ1)

All features of the e-learning platform are used in the pandemic and after the pandemic crisis and the usage of applications in 2022–2023 and 2020–2021 is similar. The use of chat is more frequent in the second year of the pandemic, but the participation in audio/video conferences and receiving feedback from teachers are more common in the first year of the pandemic. The time dedicated to learning online also decreased from the first to the second year of the research, which can be explained by going back to face-to-face classes for some of the teaching activities (seminars and workshops) at the beginning of 2021. We can also interpret these differences due to the learning efficiency felt by students while using the e-learning platform.

Table 10 Latent variable correlation matrix 2020–2021 vs. 2022–2023

2020-21 / 2022-23	ELU	LE	SAT	TSE	TC	TI	UNC
E-learning use (ELU)	1						
Learning Engagement (LE)	0.46/0.55	1					
Satisfaction (SAT)	0.55/0.58	0.72/0.74	1				
Techno self-efficacy (TSE)	0.26/0.28	0.52/0.47	0.55/0.51	1			
Technostress creators (TC)	−0.32/-0.36	−0.54/-0.50	−0.55/-0.53	−0.63/-0.55	1		
Technostress inhibitors (TI)	0.58/0.55	0.52/0.52	0.49/0.45	0.34/0.31	−0.36/-0.33	1	
Uncertainty (UNC)	−0.14/-0.22	−0.30/-0.23	−0.25/-0.21	−0.36/-0.27	0.47/0.41	−0.14/-17	1

Note All the correlations are significant at $sig < 0.001$

The reduction of the time dedicated to learning in 2022–2023 could have alternative explanations: the improvement of students' digital or academic competences, or orientation towards competing face-to face activities.

Even if in the 2021-22 academic year some universities returned to face-to-face teaching, students expected the e-learning platform to remain an important support tool. The results of our study showed that the students preferred that teachers use these applications even more, especially the features which promote autonomous learning. In 2022–2023, the frequency of using the features of the online platform compared to 2020–2021 decreased just for audio/video conferences and feedback. Some features, such as A/V resources for revising or studying on their own, solved applications, feedback or multiple-choice questions for self-assessment, seem to be more attractive than their real-life counterparts, probably increasing online satisfaction (Murphy, 2020).

Although recent studies showed that students were satisfied with teachers' activity despite challenges with technical issues (Fatani, 2020; Han et al., 2021), our study suggests differences between the students' perceptions regarding teachers' real behaviour and their expected behaviour with respect to the features used in the e-learning application. Students' expectations/preference for the use of the platform features significantly exceeds the effective use by teachers in both 2020–2021 and 2022–2023. The favourable appreciation of online learning environments was explained by the student-centred approach (Heo et al., 2021; Mader & Ming, 2015), facilitated by the audio-video conferencing system (Conboy et al., 2017), or by various representation forms of the learning materials or by the fact that the platform can be accessed anytime, from anywhere, thus allowing flexibility in learning. The difference between expectations and real platform use could be explained through the dissatisfaction with online teacher's behaviour (e.g. the tasks assigned by the teachers are not challenging enough) (Maican & Cocoradă, 2021),

Therefore, it is not surprising that students want that learning tools should be also used in the future, because the pandemic context and the online teaching and learning activities during this period have developed their skills to learn in a non-sequential way and to be more autonomous.

How did students' personal characteristics related to online learning evolve: techno self-efficacy, learning engagement, tolerance to uncertainty, and the relationships between them, in the first year of the pandemic and after the pandemic (RQ2)

Our results highlight the idea that self-efficacy can be a determinant factor of satisfaction directly and by its influence on the other determinants. This finding contrasts a recent study (Heo et al., 2021), which identified a negative effect of technology self-efficacy on online learning engagement during the Covid-19 pandemic. The positive effect found in our study highlights that promoting students' confidence in their ability to learn online could enhance learning engagement in online learning (Heo et al., 2021). As experimental studies have shown, positive changes in specific self-efficacy correspond with similar changes in levels of engagement (Ouweneel et al., 2013); therefore, it is important to invest in students' technology self-efficacy to increase

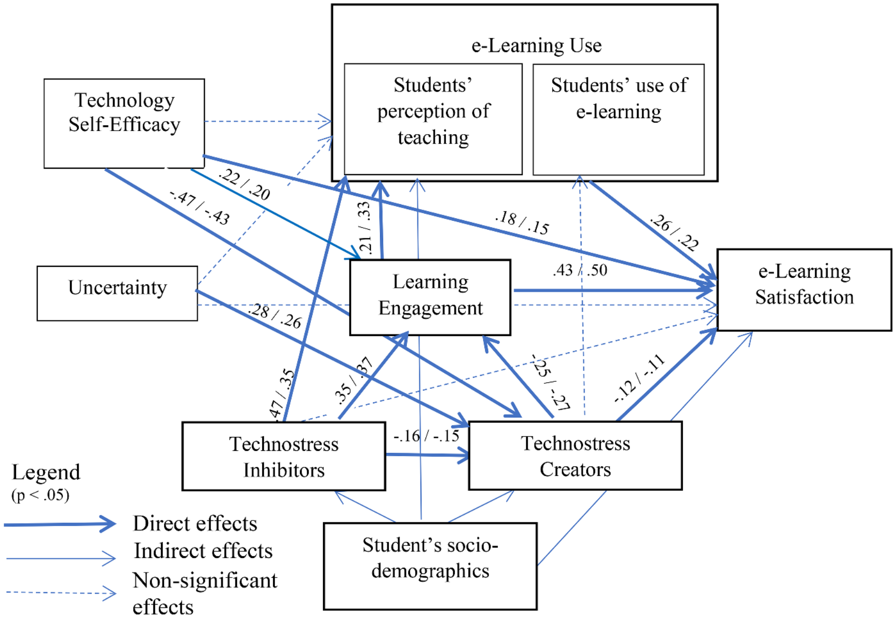

Fig. 2 The tested model. *Note* the first coefficient corresponds to the first year of the pandemic, and the second coefficient corresponds to the period after the pandemic

Table 11 a. Indirect effects of techno self-efficacy on satisfaction, and mediation type

	2020-21	Mediation type	sig	2022-23	Mediation type	sig
TSE -> ELU -> SAT	−0.008		0.618	−0.012		0.358
TSE -> LE -> ELU -> SAT	0.012	P	0.009	0.015	P	<0.001
TSE -> LE -> SAT	0.096	P	<0.001	0.102	P	<0.001
TSE -> TC -> ELU -> SAT	0.003		0.632	0.008		0.117
TSE -> TC -> LE -> ELU -> SAT	0.007	P	0.013	0.009	P	<0.001
TSE -> TC -> LE -> SAT	0.052	P	<0.001	0.059	P	<0.001
TSE -> TC -> SAT	0.057	P	0.007	0.050	P	0.001

Note LE=learning engagement; Sat=Satisfaction; TSE=Technology Self-Efficacy; TC=Technostress Creators; TI=Technostress Inhibitors; UNC=Uncertainty; ELU=E-learning Use. P=partial mediation

their levels of engagement. On the other hand, the relationship between technology self-efficacy and engagement could be mediated by other factors such as online self-regulated learning strategies, an aspect which could be investigated in future studies.

The current results did not show a direct significant effect of technology self-efficacy on e-learning use, and the mediated effects were weak; this result may be to the mandatory use of e-learning during the crisis-period, even though some students may not have known-how to use technology. However, a result worth mentioning is the positive significant effect of technology self-efficacy on learning engagement. Previous studies also support the positive effects of academic self-efficacy on learning engagement (Linnenbrink & Pintrich, 2003; She et al., 2021), but the relationship

Table 11 b. Indirect effects and mediation type for technostress creators and inhibitors on satisfaction

	2020-21	Mediation type	sig	2022-23	Mediation type	sig
TC -> E-LU -> SAT	−0.007		0.632	−0.018		0.122
TC -> LE -> E-LU -> SAT	−0.014	P	0.011	−0.021	P	<0.001
TC -> LE -> SAT	−0.110	P	<0.001	−0.135	P	<0.001
TI -> E-LU -> SAT	0.122	T	<0.001	0.081	T	<0.001
TI -> LE -> E-LU -> SAT	0.020	T	0.004	0.028	T	<0.001
TI -> LE -> SAT	0.154	T	<0.001	0.185	T	<0.001
TI -> TC -> ELU -> SAT	*0.001*		0.646	0.003		0.128
TI -> TC -> LE -> E-LU -> SAT	0.002	P	0.020	0.003	P	0.001
TI -> TC -> LE -> SAT	0.018	P	0.001	0.020	P	<0.001
TI -> TC -> SAT	0.019	P	0.014	0.017	P	0.004

Note LE=learning engagement; Sat=Satisfaction; TSE=Technology Self-Efficacy; TC=Technostress Creators; TI=Technostress Inhibitors; UNC=Uncertainty; E-LU=E-learning use. T=total mediation, P=partial mediation, NS=mediation effect not significant

Table 11 c. Indirect effects and mediation type from Uncertainty to Satisfaction

	2020-21	Mediation type	sig	2022-23	Mediation type	sig
UNC -> ELU -> SAT	−0.002		0.874	−0.015		0.106
UNC -> LE -> ELU -> SAT	−0.003		0.249	<0.001		0.857
UNC -> LE -> SAT	−0.022		0.144	−0.003		0.843
UNC -> TC -> ELU -> SAT	−0.002		0.638	−0.005		0.169
UNC -> TC -> LE -> ELU -> SAT	−0.004	P	0.019	−0.005	P	0.001
UNC -> TC -> LE -> SAT	−0.031	P	<0.001	−0.036	P	<0.001
UNC -> TC -> SAT	−0.033	P	0.005	−0.030	P	0.008

Note E=learning engagement; Sat=Satisfaction; TSE=Technology Self-Efficacy; TC=Technostress Creators; TI=Technostress Inhibitors; UNC=Uncertainty; ELU=E-learning use. Mediation type: T=total mediation, P=partial mediation

between technology self-efficacy (specific self-efficacy) and e-learning engagement has not been extensively investigated so far. According to Social Cognitive Theory, individual's behaviour is regulated by a combination of some external and internal factors (Bandura, 2012), of which self-efficacy has the most prominent influence on behaviour.

Using insights from (Bandura, 2012), we can explain the absence of the direct effect of techno self-efficacy on e-learning use by: (i) difficulties to distinguish between self-efficacy during their acquisitional phases and the performance of acquired skills - although the students are digital natives, they are not fully competent in using e-learning platforms, and some of them had to learn these skills in the pandemic time; (ii) e-learning being a mandatory environment, the students do not have direct control over conditions, and consequently their satisfaction depends on the interdependent efforts of students, teachers, peers and the chosen e-learning features. Additionally, the self-efficacy scale does not distinguish between simple and

Table 12 Multigroup analysis: Total Effects and Path Coefficients (only significant values are shown, $p < .05$)

	Total effects	Path Coefficients
2020-21_F – 2022-23_F		
Learning Engagement -> Satisfaction	−0.174	−0.144
Technostress inhibitors -> e-Learning use	-	0.249
Technostress inhibitors -> Learning Engagement	−0.126	−0.125
Uncertainty -> Learning Engagement	−0.137	−0.129
2020-21_SSHA – 2022-23_SSHA		
Learning Engagement -> Satisfaction	−0.179	−0.163
Technology self-efficacy -> Learning Engagement	-	0.167
Technostress Creators -> Satisfaction	-	−0.132
Technostress inhibitors -> e-Learning use	0.178	0.242
Uncertainty -> e-Learning use	0.253	0.240
F – M		
2020-21_F – 2020-21_M		
Technostress Creators -> e-Learning use	0.325	0.256
Technostress inhibitors -> e-Learning use	0.201	0.287
Uncertainty -> Learning Engagement	-	−0.158
2022-23_F – 2022-23_M		
Technostress Creators -> e-Learning use	0.214	-
Technostress inhibitors -> Learning Engagement	0.175	0.174
Technology self-efficacy -> e-Learning use	-	0.269

Note M = Male, F = Female, SSHA = social sciences, humanities, arts, ($p < .05$)

sophisticated online tasks, and the items may have been interpreted by students in either way, given that they are not specific.

Uncertainty increases techno creators, but it does not influence students' satisfaction directly. Its effects remain negative when the relations are mediated by learning engagement, and E-learning use. Intolerance to uncertainty is associated with anxiety (Carleton et al., 2012) and high levels of anxiety could negatively affect motivation and achievement (Heckel & Ringeisen, 2019), which could explain the buffer effect of uncertainty on the relationship between students' personal factors and online learning satisfaction.

The analysis of the role of learning engagement as a mediator in the context of e-learning satisfaction, especially during and after the pandemic, provides interesting insights into the dynamics of online education. Particularly, the current results indicate that learning engagement directly influences e-learning satisfaction and plays a significant role in mediating the effects of other factors such as technology self-efficacy and technostress on satisfaction, e.g. (Santoso, 2021).

The positive effect of technology self-efficacy on learning engagement highlights the importance of students' confidence in their abilities to use technology for learning, directly enhancing engagement, which, in turn, leads to higher satisfaction with the e-learning experience (e.g. (J.-W. Lee & Mendlinger, 2011; Prifti, 2022). The findings suggest that, when students feel competent in navigating e-learning platforms and using their features, they are more likely to engage deeply with the learning content, thereby enhancing their overall satisfaction.

Furthermore, learning engagement diminishes the direct negative effect from technostress creators to satisfaction (Tarafdar et al., 2010). In environments where technostress is present, the role of engagement becomes important. Students who can maintain high levels of engagement in the face of technostress are likely to experience higher satisfaction levels. The partial and serial mediations involving learning engagement, e-learning use, and technostress inhibitors further illustrate the complex interactions between these factors. Engagement not only serves as a direct contributor to satisfaction, but also as an enhancer that brings positive effects of technostress inhibitors on satisfaction, suggesting that interventions aimed at increasing engagement could have extensive benefits across many aspects of the e-learning experience.

RQ3. How was students' satisfaction influenced by techno stress (creators and inhibitors) and by their personal and socio-demographic characteristics in the first year of the pandemic and after the pandemic?

According to our hypothesis, technostress creators have negative effects on learning engagement, and e-learning use. Some students may not have all the up-to-date technology, and this may put them at a disadvantage. Additionally, the invasion of technology in learning was associated with a decrease in self-efficacy and cognitive engagement, the challenges of the online activities leading also to pandemic-related anxiety and stress and to a decrease of the satisfaction towards the academic activity (Bolatov et al., 2021; Aguilera-Hermida, 2020).

These can also be seen in the differences between 2020 and 2021 and 2022–2023, between genders, confirming previous studies (Salanova et al., 2013) or between fields of study (SSHA vs. STEM) in terms of computer anxiety seen as part of technostress creators (Maican & Cocoradă, 2017). These results could offer an input to universities to allocate resources on providing students with sufficient, concise and well-organized information which will not only increase the perceptions of usefulness and satisfaction towards e-learning tools but will also enhance students' engagement (Al-Fraihat et al., 2020).

The current results confirm the stress literature on the negative relationship between job/study demands (technostress creators) and learning engagement, an excessive level of technostress decreasing learning engagement. Technostress inhibitors have a direct effect on e-learning use and predict a high level of students' engagement in learning and e-learning use, in line with previous research, showing that job/study resources could increase the learning engagement level (Bakker & Demerouti, 2008, 2017; Chen, 2017a,b; Wöhrmann & Ebner, 2021). These influences can be noticed in both years of the study and in the findings regarding gender differences. Thus, in 2020, the use of online applications was something relatively new, the technical support provided explaining the greater use of online applications. In 2022–2023, the effect of novelty waned, but students began to identify the usefulness of online applications both in remote teaching-learning and in face-to-face learning, which may explain the stronger positive effect of technostress inhibitors on learning engagement rather than on the actual use of applications. Previous studies also identified student enjoyment with the prior use of e-learning tools and their positive effects on the learning engagement during the pandemic (Kemp et al., 2019; Aguilera-Hermida, 2020).

Our study identified specific effects on the satisfaction of using e-learning considering socio-demographic factors such as gender and field of study, confirming previous studies (Z. Yu, 2022). Also, recent studies have argued that students used more online educational tools after the transition to online learning than before. The use of emergency e-learning programs increased students' knowledge of technological tools (Murphy, 2020), their experience and technological skills improved, the emergency remote teaching specific for the first period of the Covid-19 pandemic was replaced with a more systematic and organised online teaching which could explain the higher satisfaction towards online learning and teaching in 2021.

At the beginning of the pandemic, most of the students used online systems without any preparation, their learning motivation, self-efficacy and cognitive engagement, and subsequently their satisfaction was low (Aguilera-Hermida, 2020), as also revealed in the first year of our study. As time went by, the use of applications began to be more refined and more appropriate to students' needs, which led to an increase in satisfaction in 2022–2023 compared to 2020–2021. Also, in 2022–2023 students became accustomed to online teaching and the use of the various features in the platform, this being obvious especially in SSHA. Girls in 2022–2023 used applications and resources that inhibited stress, and were more active, but uncertainty reduced their learning engagement. They learned from their previous experience, including the use of the platform and apps, and thus their satisfaction increased. It is possible that this satisfaction with e-learning will continue in the future.

Contributions

This study may contribute to the knowledge and practice on technostress and learning engagement. First, the job-demand-resources framework, seen as "study-demands-resources" in the current study, has been little used in the education field, even though the similarities between job-study situations are important. From the perspective of this framework, we have seen technostress creators as study-demands and technostress inhibitors as study-resources. The effects of these variables on satisfaction confirm the correctness of our choice.

Second, techno-inhibitors are little researched among students, perhaps because institutions believe that IT support is more useful for teachers who are not as familiar with technology as students. At the same time, the role of students can be seen as a passive one, as receivers of the content delivered electronically by the teacher through the conference and, in this capacity, the students can manage to get by. However, our results show that students also feel the stress generated using technology, manifest intolerance to uncertainty, which can affect their involvement in learning and their satisfaction. We considered it necessary to focus on the student IT skills, the engagement and autonomy of the learner being critical in online learning.

Third, previous research regarding intolerance to uncertainty among students and especially in the context of learning is not sufficiently developed. Although uncertainty is generated by the pandemic, as a factor resulting from the person-situation interaction, uncertainty is not manifest directly over the satisfaction of using e-learning, but only through technology. We see, therefore, its role as an indirect "influencer" in certain situations. This aspect is the more important as in certain regions of the world the state of uncertainty associated to various events at the macrosocial level is maintained (conflicts, environmental issues, various types of disasters and crises).

Forth, comparing the two-year data of the pandemic on the same general student population, we identified important aspects that can be a starting point for the further use of technology and its efficient integration in teaching activities, e.g., the difference between SSHA and STEM in 2020–2021 in terms of the effects of technostress on learning engagement, or M/F differences.

Also, the assessment of e-learning tools was one of the most researched topics in education in the context of the Covid-19 pandemic, as the number and the variety of e-learning tools increased. Most of the studies have examined individual aspects of e-learning systems success, such as system quality (Al Mulhem, 2020), information and service quality (Dwidienawati et al., 2020) and their relationships with satisfaction and usefulness, or the relationships between e-learning quality factors and usage or satisfaction e.g. (Cheng, 2020; Puriwat & Tripopsakul, 2021; Saxena et al., 2021). Thus, lastly, we adapted a tool for learning (Annex 1) that measures *Students' use of e-learning* (use of platform features by students, in our study), and *Student perception of teaching*, respectively. Our results reconfirm it as a useful tool through associations with other tools or by highlighting some STEM-SSHA, F-M differences.

Implications

Before the pandemic, the main purpose of distance and online education was to provide access to training for those who otherwise could not participate in a traditional face-to-face academic program. The flexibility and learning opportunities necessitated by social distancing are likely to alter the expectations of both students and teachers, blurring the distinction between classroom instruction and e-learning even further. Under the conditions of using online or hybrid learning, universities need to make sure students are comfortable engaging and interacting online. Therefore, universities and teachers ought to know students' needs related to using e-learning platforms, to improve their skills simultaneously with an increase in technology self-efficacy, even if some students are "digital natives".

With the return to face-to-face education, we expect the platforms to continue to be used (as they promote autonomous learning, communication/collaboration, assignments etc.). In addition, from a managerial point of view, investments to improve platforms, maintaining available equipment, and online tools must continue.

Teachers need to improve both the classical pedagogical approach and the online one and keep the differences between them. They must rethink their teaching methods in the online environment, adopt them to specific subjects and students' needs, and develop their techno competences to regulate learning. Their satisfaction with the prior use of e-learning tools could have positive effects on their motivation and learning engagement.

Students who have spent two years using e-learning feel less stressed and more comfortable with using the technology, and this means that they need less guidance and support in performing their responsibilities or solving the tasks. At the same time, students' expectations/preference for the use of the platform features significantly exceeds the actual use by teachers in both 2020–2021 and 2022–2023, even after the return to face-to-face learning. It is possible that these students could have the same expectations at work, by using online communication/ collaboration tools. They could even adapt to remote working quickly and efficiently, a fact whose development started by using autonomous learning features in online platforms.

Intolerance to uncertainty is associated with anxiety - students have become aware of their own level of technology-related anxiety and they have learned how to handle it to lower the level of stress. Consequently, teachers and managers can deal with more conscious individuals about their own limits and could offer support depending on the needs of the student. At the same time, uncertainty and rapid change will remain a feature of the education system and of life at large, so it is necessary to implement strategies to increase uncertainty tolerance, reduce the negative effects of distress on learning engagement and satisfaction to use learning platforms.

Limitations and future research directions

This is not a longitudinal study because it does not compare the changes from one year to another for the same participants. Our choice for a study focused on different groups from different years to the detriment of a design with paired samples was determined by the need to ensure the anonymity of the data collected at the beginning of the pandemic, in a context marked by many uncertainties, fears and excessive use of technology. However, the present study is important since it shows the differences regarding the use of technology and student behaviour in learning, the positive transformations regarding learning engagement and learning satisfaction considering two important moments: the pandemic period (academic year 2020–2021) and the post-pandemic period (2022–2023).

The self-report measures used in our study can introduce errors that could be exacerbated by many items. The study could be completed with further objective measures, such as direct indicators of the use of e-learning platforms: log analysis, time spent online etc., accompanied by qualitative studies. Future studies could also include measures of student performance, such as grades, completion and drop-out rates.

Given the future use of online learning platforms, a more comprehensive tool would allow the assessment not only of self-regulation learning strategies, but also of IT skills and confidence. Based on a more complete diagnosis, students would develop their personal resources to diversify the support provided. Although the developed tool is a valid one, with a high predictive value, a future direction of research could be the development of a short version.

Conclusions

The recent pandemic period came to an end, but the use of e-learning will surely remain a constancy in teaching and learning. E-learning satisfaction increases in students with higher technology self-efficacy when inhibitors act, but it decreases in the presence of stress creators and uncertainty. Student engagement is the strongest and most frequent mediator for satisfaction, decreasing the direct negative effect of stressors.

The comparative approach between the two periods showed, on the one hand, many similar patterns in the two years, but also some significant differences. Even though the COVID-19 continued past 2020, online teaching skills have changed, and students' expectations have evolved simultaneously with their online learning and involvement skills. This was an important starting point for the use of technology in teaching-learning and of the same technologies in circumstances of digitalized learning, which has been maintained even after the end of the pandemic, digitalization being a natural trend of today's society.

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Declarations

Ethics approval All ethical guidelines were followed as required for conducting human research.

Consent for publication We confirm that the article has not been published elsewhere, nor is it currently being considered for publication.

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interests.

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