Balancing the Digital Load:
Exploring the Role of ICT Services and Technostress Inhibitors in Student Satisfaction With E-Learning

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ABSTRACT

This study examines how online learning affects student satisfaction, focusing on technostress creators and inhibitors across two academic years—2020 (initial e-learning phase) and 2023 (post-familiarization). Using a mixed-methods design, quantitative data from 1,470 digital-native students and qualitative IT help messages were analyzed. Results show higher satisfaction in 2023 and among women, though platform usage remained steady across years and was higher among women. Technostress was greater in 2020 and among women, but technostress inhibitors gained importance over time, especially for men. Digital literacy support positively influenced both usage and satisfaction. Overall, technostress inhibitors play a key role in improving online learning experiences, with practical and theoretical implications discussed.

KEYWORDS

Online Learning, Satisfaction, Technostress Creators, Technostress Inhibitors, University Students

INTRODUCTION

In recent years, the widespread adoption of information and communication technologies (ICT) has been greatly recommended by countries within the Organization for Economic Cooperation and Development (OECD, 2023) and has become a priority for the European Union (2021). However, in the post-COVID era, the pace of digital education has slowed or even stopped in some zones while growing in others. These choices can be explained by diversified adjustments to digital environments, the varied consequences of social inequalities, concerns about students' mental health and well-being, and teachers' demand and response in emergency situations (Butler et al., 2024). The decision to continue the development of digital education is argued by the opportunity to support hybrid learning practices, enhance teaching and learning processes, and ensure that students and teachers are equipped with the digital skills to adapt in an increasingly digitized labor market. Furthermore, this approach may increase the responsiveness of education systems in times of uncertainty and change (European

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Commission et al. 2023, 2023; OECD, 2023). Growing or stopping digital education raises questions about the rationale for these opposing policy decisions and their long-term consequences.

A central challenge within this digital ecosystem is technostress. As a result of threatened or actual technological demands that exert significant effects on students' coping capabilities, technostress can impact students by reducing satisfaction (Cofini et al., 2022; Nastjuk et al., 2024) and diminishing both the quality of online learning and student well-being (Asensio-Martínez et al., 2023; Saleem et al., 2024), as well organizational effectiveness (Tarafdar et al., 2019). The existing literature presents a complex and sometimes contradictory picture of how technostress relates with personal traits, including self-efficacy, engagement, and sociodemographic factors (Al Shamsi, 2024; Alshammari, 2020). For instance, findings on gender differences in technostress are inconsistent (Šorgo et al., 2022; Upadhyaya & Vrinda, 2021; Wang et al., 2021). To mitigate these stressors, universities can implement technostress inhibitors—institutional resources provided by ICT departments (Lanzl, 2023). These institutional mechanisms, such as technical support and literacy facilitation, are designed to mitigate technology-related strain and improve user satisfaction (DeLone & McLean, 2003; Faize & Nawaz, 2020; Lanzl, 2023; Ragu-Nathan et al., 2008).

However, the effectiveness of these resources depends on students' ability to actively access and utilize them, which introduces the critical role of help-seeking behavior. The literature reveals a complex picture, as both the propensity to experience technostress and the willingness to seek help are often influenced by individual and sociodemographic traits. Studies show that male students, in particular, may be more reluctant to seek technical assistance (Hadad, 2025; Koc & Liu, 2016). This suggests a potential disconnect: the very students who might need support may be the least likely to ask for it. Thus, understanding how different student groups perceive and engage with both technological demands and institutional resources is essential for designing effective interventions.

Significant gaps remain in our understanding related to technostressors and technoinhibitors. First, there is limited comparative research examining how students' perceptions of ICT support have evolved from the initial, mandatory shift to e-learning in 2020 to a more familiarized stage in 2023. Second, specialized literature is dominated by cross-sectional studies, which fail to capture the dynamic nature of student adaptation over time. Finally, many studies focus on broad measures of usability, with insufficient exploration into how specific technostress creators and inhibitors function at a more granular level (Nastjuk et al., 2024; Simon et al., 2023).

The present study addresses these gaps through a two-wave study that examines both aggregated and disaggregated data. Looking at the transition from the pandemic era to a more digitally integrated educational environment is needed, as the perception of technostress and the effectiveness of technological inhibitors may evolve, disappear, or emerge over time (Berger et al., 2024).

While students born after 1980 are often categorized as "digital natives" and considered to be proficient with technology (Cahyono et al., 2022; Prensky, 2001), such perceptions mask significant underlying complexities. Other research indicates that students' technological skills are heterogeneous (Upadhyaya & Vrinda, 2021), and disparities in technology access persist (United Nations Educational, Scientific and Cultural Organization, 2020). Although students frequently use technology for entertainment and social interaction, their use of a university's learning management system (LMS)—the central platform for academic activities—is less well understood (Nastjuk et al., 2024). These inconsistencies in digital skills and adaptation underscore the need for further investigation to develop refined, evidence-based practices.

This study aims to explore the dynamic relationship between technostress, LMS usage, and satisfaction among digital-native students, considering gender and field of study. By comparing the experiences of university students during the initial, mandatory shift to e-learning (the pandemic period) with those in a subsequent period of familiarization (the post-pandemic period), it seeks to provide critical insights into how these experiences have evolved. The inclusion of qualitative data from information technology support tickets alongside quantitative survey measures offers a more nuanced understanding of these dynamics. Specifically, by focusing on the role of technoinhibitors (such as institutional resources like information technology support) in mitigating the impact of technology-related stressors, this study provides practical organizational and technical insights intended for professors, information technology managers, and institutional decision-makers. The study's primary contribution is its adoption of this comparative approach to reveal the evolving nature of students' adaptation to technology and to provide actionable guidance for improving long-term digital learning.

According to the study's objective, the following research questions were formulated:

- **RQ1:** How did gender and field of study influence the evolution of LMS usage and student satisfaction from the initial emergency phase in 2020 to the familiarization period in 2023?
- **RQ2:** How did gender and field of study influence students' perceptions of specific technostress creators and technoinhibitors across these two periods?
- **RQ3:** What were the key predictors and mediators of LMS use and satisfaction in the online environment during these periods?
- **RQ4:** What specific LMS-related issues prompted students to request help from the information technology department?

HYPOTHESES DEVELOPMENT AND MODEL RESEARCH

Use of E-Learning Platforms and Satisfaction

The adoption of e-learning platforms has reshaped education by offering numerous digital services. LMS provide tools for enrollment, course materials, discussion groups, communication, and assessments (Bradley, 2021). However, technical challenges such as poor audio or video quality, login issues, and slow internet connections—along with home-based distractions—have reinforced existing inequalities between groups and regions (Dhawan, 2020; Faize & Nawaz, 2020; Roman & Plopeanu, 2021). These disparities have negatively impacted students' e-learning experiences (Selwyn, 2023) and influenced the decisions of university management regarding whether to continue or stop online learning (Butler et al., 2024).

While the acceptance of LMS is influenced by a range of factors—including perceived usefulness, social influence, and facilitating conditions (Venkatesh et al., 2003)— students' personal characteristics such as gender, age, ICT experience, self-efficacy, and coping strategies remain key areas of investigation. Prior research has presented inconsistent findings regarding the impact of traits like gender and field of study on e-learning engagement. Some studies reported no significant gender-related differences (Shams et al., 2022), while others suggested that women may be more effective in online learning due to higher conscientiousness (Verbree et al., 2023), or, conversely, that men exhibit greater technical confidence (Abdous, 2019). Similarly, STEM students have been found to adapt more favorably to e-learning than their peers in other fields (Al Shamsi, 2024). Moreover, perceptions of COVID and associated social risks also influenced students' decisions to adopt online learning (Guo et al., 2024). Under these conditions, the following hypotheses were formulated related to RQ1:

- **H1.1:** Gender and field of study have a significant effect on LMS usage, with (a) women and (b) SSHA students using LMS more frequently than men and STEM students (RQ1).

Regarding changes over time, the mandatory nature of the e-learning environment during both study periods suggests that usage levels were primarily dictated by course requirements rather than user choice (Zhang et al., 2020). Therefore, overall frequency of use is expected to remain consistent.

- **H1.2:** Students use LMS at similar levels during both the initial mandatory online learning phase and the subsequent period of familiarization (RQ1).

The adaptation process may not be uniform across all student groups. The initial difficulties or obstacles of online learning might affect different demographics in distinct ways. Therefore, we posit an interaction effect:

- **H1.3:** There is a statistical interaction between year of research and (a) gender or (b) field of study in LMS use (RQ1).

While acceptance is a necessary condition for a successful Information System (IS), it is not sufficient. Consequently, satisfaction and its relationship with system usage are considered key measures of IS success (Al-Fraihat et al., 2020; DeLone & McLean, 2003). In educational contexts, student satisfaction with the learning experience is a primary institutional goal. Learning satisfaction was defined as student's attitude toward their educational experience, facilities, and services, or the mood resulting from their evaluation of this experience (Weerasinghe & Fernano, 2018). Satisfaction with LMS is influenced by factors such as their level of participation (Zhai et al., 2023), familiarity with the platform (Wang, 2020), and level of perceived stress, as well as users' personal traits (Cofini et al., 2022; Ionescu et al., 2023). As with LMS usage, the literature on gender differences in satisfaction is varied, with some studies reporting higher satisfaction among men (Lu & Chiou, 2010) and others finding the opposite (Abdous, 2019; Wang et al., 2020). Consistent with our hypothesis that women and social science, humanities, and arts (SSHA) students will exhibit greater LMS use (H1.1), we anticipate higher satisfaction with the learning experience. In line with these findings, we have assumed:

- **H2.1:** Gender and field of study significantly impact LMS satisfaction, with (a) women and (b) SSHA students reporting higher satisfaction than men and STEM students, respectively (RQ1).

Over time, student satisfaction is expected to improve as they surmount initial technical and procedural hurdles. Increased familiarity with LMS should lead to a more positive appraisal of its role in their learning process. Therefore, this study proposes:

- **H2.2:** The year of research significantly affects satisfaction, with students reporting lower satisfaction during the initial mandatory e-learning phase compared to the period of familiarization (RQ1).

Finally, it is hypothesized that the change in satisfaction levels between the two periods will not be uniform across all student groups, reflecting diverse adaptation patterns.

- **H2.3:** There is a statistical interaction between the year of research and (a) gender and (b) field of study in predicting satisfaction (RQ1).

Perceptions of Technostress Creators (Demands)

To analyze the pressures of the digital learning environment, this study adopts the perspective of job demands and resources (Bakker et al., 2023). According to the theoretical framework, a perceived imbalance between the demands of a job and the resources available to manage them leads to increased effort and strain.

In online learning settings, job demands are conceptualized as technostress creators—specific technology-related aspects of the e-learning environment that require sustained student effort and consume cognitive or emotional energy. A perceived mismatch between these technological demands and students' personal or institutional resources can lead to technostress (Kumar, 2024; Ragu-Nathan et al., 2008).

Drawing from previous literature, these technostress creators were operationalized through five facets (Ragu-Nathan et al., 2008; Roman & Plopeanu, 2021; Tarafdar et al., 2019): (1) techno-overload (technology forces one to work faster and longer); (2) technocomplexity (technology is too complex and requires a high level of skill); (3) technoinsecurity (fear that an individual's skills may become obsolete due to new technologies); (4) technoinvasion (constant connectivity with technology forcing individuals to always be available); and (5) technouncertainty (negative emotions and confusion in the context of continuous technological changes and need to adapt).

Gender differences in perception of technostressors are inconsistent across studies, with some reporting lower levels of technostress in men (Wang et al., 2021), others higher among women (Šorgo et al., 2022), and some finding no significant differences (Asensio-Martínez et al., 2023; Ragu-Nathan et al., 2008; Tarafdar et al., 2011). Women report greater stress in technocomplexity and technouncertainty, influenced by technology engagement, anxiety, social inequalities (Abdous, 2019; Qazi et al., 2022). Higher technostress was perceived by students with lower ICT experience (Upadhyaya & Vrinda, 2021) and with broader cultural and organizational factors, such as high masculinity, power distance, and competition (Ma & Turel, 2019; Turel & Gaudioso, 2018).

Under these conditions, the study proposes the following hypotheses:

- **H3.1:** Gender and field of study significantly influence perceptions of technostress creators, with (a) women and (b) SSHA students perceiving higher levels of technostress creators compared to men and STEM students (RQ2).

The initial, abrupt transition to mandatory e-learning in 2020 was characterized by high uncertainty and numerous technical challenges Additionally, according to the transactional theory of stress and coping, the stress results from the individual's appraisal of events in relation to their available resources. Changing the appraisal of situations or events may diminish maladaptive reactions and increase adaptation (Lazarus & Folkman, 1984). As students and institutions adapted to digital learning, it is anticipated that this initial stress would have diminished.

- **H3.2:** The year of research has a significant effect on the perception of technostress creators, with students perceiving higher technostress during the initial mandatory e-learning phase than after becoming familiarized with the environment (RQ2). This adaptation process, however, may not have been uniform across all demographic groups.
- **H3.3:** There is a statistical interaction between year of research and (a) gender and (b) field of study in the perception of technostress creators (RQ2).

Perceptions of Technostress Inhibitors (Resources)

Drawing on the complementary relationship between job demands and resources, the theoretical framework by Tarafdar et al. (2019) suggests that while ICT can generate technostress, it can also be expanded to mitigate its threatening effects and enhance its beneficial outcomes. In contrast to technostress creators, technoinhibitors function as organizational resources that help individuals manage demands, achieve goals, and increase satisfaction in university settings (Alshammari, 2020; Ragu-Nathan et al., 2008; Tarafdar et al., 2011). Inhibitors include technical support, which provides timely assistance for technology-related issues; literacy facilitation, which offers resources and training to develop digital skills; and involvement facilitation, which enables students to influence decisions about the technologies they use, giving them a sense of control and ownership (Hang et al., 2022; Ragu-Nathan et al., 2008).

Help-seeking behaviors, which are critical for accessing organizational resources, often differ by gender. Research suggests that women are more likely to seek assistance, whereas men may be more reluctant, partly due to social stereotypes that emphasize independence (Koc & Liu, 2016; Korlat et al., 2021). This suggests that groups more willing to seek help may also evaluate support systems more favorably. Building on H3 and past literature, H4 was proposed:

- **H4.1:** Gender and field of study significantly influence perceptions of technoinhibitors, with (a) women and (b) SSHA students expected to have a more favorable appraisal of technostress inhibitors compared to men and STEM students (RQ2).

During the initial phase of online learning, students may have been unaware of the full range of available support or hesitant to use it. With time and experience, their recognition and appreciation of these inhibitors likely increased.

- **H4.2:** The year of research has a significant effect on the perception of technoinhibitors, with students appraising them more favorably after extended exposure to compulsory online learning compared to the initial period (RQ2).

As with technostress creators, the evolution of these perceptions is expected to vary across different student populations.

- **H4.3:** There is a significant interaction between the year of research and (a) gender or (b) field of study in the perception of technoinhibitors (RQ2).

Increasing LMS Use and Satisfaction With Online Learning

Certain technostressors—such as overload, complexity, and insecurity—have a negative impact on user satisfaction (Abd Aziz et al., 2023; Cofini et al., 2022; Šorgo et al., 2022). However, their effects can be both positive and negative, particularly in organizational contexts (Nastjuk et al., 2024; Tarafdar et al., 2011). To improve student satisfaction, universities have implemented successful technical interventions. Factors such as developing user-friendly systems (Mohammed et al., 2022), ensuring high-quality information technology services (Machado-Da-Silva et al., 2014), integrating student feedback (Faize & Nawaz, 2020), and providing student workshops, training, or instruction to manage online learning demands (Saleem et al., 2024) have been effective in reducing technostressors (Lanzl, 2023). Technostress inhibitors mediate the relationship between technostress and students' well-being (Asensio-Martínez et al., 2023) and improve online learning quality (Saleem et al., 2024; Tarafdar et al., 2011). However, past studies have found no significant effect of technostress inhibitors on these relationships (Ragu-Nathan et al., 2008).

To investigate the predictive relationships among the explored variables, this research posits that technostress creators function as "demands" that negatively impact key success outcomes (LMS use and satisfaction), while technoinhibitors act as "resources" that both directly support these outcomes and buffer the negative effects of the demands. Thus, within the job demands-resources (JD-R) framework—which conceptualizes how job demands create strain while resources help mitigate it—resources are expected to directly counteract demands. Therefore, this study hypothesizes that institutional support systems should reduce the level of stress perceived by students.

- **H5.1:** Technostress inhibitors negatively predict the perception of technostress creators (RQ3).

Next, the study examines the direct effects of these demands and resources on LMS use and satisfaction. Technostress creators are expected to impair students' ability and motivation to use LMS. Furthermore, research consistently shows that stressors such as overload, complexity, and insecurity have a clear negative impact on user satisfaction (Abd Aziz et al., 2023; Cofini et al., 2022; Šorgo et al., 2022). On the other hand, technoinhibitors can make the technology more accessible and understandable, improving user satisfaction. In line with these findings, the following is proposed:

- **H5.2:** LMS use is (a) negatively predicted by technostress creators and (b) positively predicted by technoinhibitors.
- **H5.3:** LMS satisfaction is (a) negatively predicted by technostress creators and (b) positively predicted by technoinhibitors.

A central aim of this study is to test the relationship between LMS use and user satisfaction. Positive experiences with the system (satisfaction) encourage further use. In turn, increased use leads to greater satisfaction. Thus, the following hypothesis was proposed:

- **H5.4:** LMS use and satisfaction are mutually predictive.

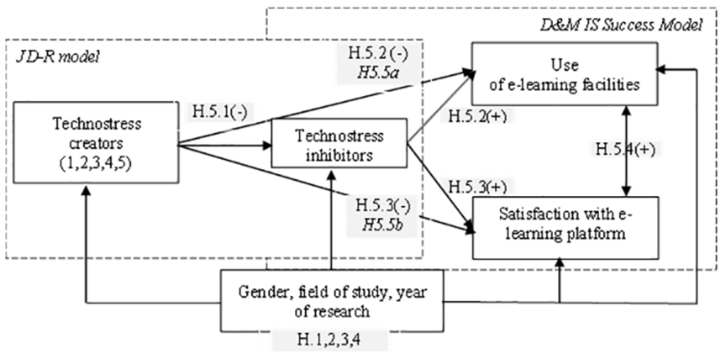
According to the JD-R theory, job demands and resources influence outcomes such as satisfaction and well-being both independently (as direct effects) and interactively (Bakker et al., 2023). This interactive component (the "buffering hypothesis") proposes that resources not only directly impact outcomes but also weaken the negative relationship between demands (technostress creators) and those outcomes, such as LMS use and satisfaction. In the context of this research, this interaction implies a mediating role for technoinhibitors. While some past research found no significant mediating effect for inhibitors (Ragu-Nathan et al., 2008), more recent studies support their mediating role in improving well-being and learning quality (Asensio-Martínez et al., 2023; Saleem et al., 2024; Tarafdar et al., 2011). Therefore, the study hypothesizes:

- **H5.5:** Technostress inhibitors mediate the relationships between technostress creators and (a) LMS use and (b) LMS satisfaction.

Model Research

The hypotheses developed in the preceding sections are consolidated into the integrated research model depicted in Figure 1. This model synthesizes two established theoretical frameworks—the DeLone & McLean (D&M) information systems success model and the JD-R model—providing a comprehensive view of the factors that influence student outcomes within a mandatory e-learning environment.

Figure 1. Integrated research model



Note. H = hypothesis and its number; (+) / (–) show a positive or negative relation; words in italic show the hypothesis focused on mediation relation.

The D&M model provides the core outcome variables for this study—use of e-learning facilities and satisfaction with the e-learning platform—along with their proposed reciprocal relationship (H5.4; DeLone & McLean, 2003). The JD-R model, in turn, provides the primary explanatory mechanism (Bakker & Demerouti, 2023). It frames technostress creators as "demands" (aspects of the system that induce strain) and technoinhibitors as "resources" (institutional supports that mitigate strain and facilitate goals; Ragu-Nathan et al., 2008; Tarafdar et al., 2019). These constructs are hypothesized to predict the outcomes both directly (H5.2, H5.3) and indirectly through mediation (H5.1, H5.5).

An important aspect of this study is the adaptation of the combined framework to the unique context of mandatory online learning during and after the COVID-19 pandemic. Typically, these models have been applied in organizational settings where technology use is often optional and performed by employees (e.g., Venkatesh et al., 2003). In this study, the "users" are students, the "work" is learning, and the use of LMS is non-volitional. This contextual shift may alter the dynamics between demands, resources, and outcomes, providing a novel test of the robustness of the quoted theories.

Finally, the current model incorporates student characteristics (gender, field of study, and year of research) as direct predictors. This inclusion allows for an examination of how these demographic variables influence the constructs of use, satisfaction, and perceptions of technostress, aligning with hypotheses H1 through H4. Overall, this integrated model provides a comprehensive framework for testing how technological pressures and institutional support shape the dynamics of learning outcomes.

MATERIALS AND METHODS

Research Design and Context

This study employed a two-wave, comparative cross-sectional mixed-methods design. This approach was chosen to analyze and compare the experiences of two independent student samples at distinct moments in their adaptation to mandatory e-learning, thus avoiding the potential attrition and testing-effect biases common in longitudinal panel studies. The justification for the temporal spacing is central to the research objectives.

Wave 1 (May–July 2020) was timed to capture the initial, high-stress emergency transition to compulsory online learning during the global pandemic. This sample represents a baseline of user experience under conditions of high uncertainty and low familiarity.

Wave 2 (April–May 2023) was conducted to assess a sample that had become fully accustomed to a normalized and routinized digital learning environment. This interval allowed time for significant institutional and personal adaptation, providing a meaningful point of comparison to assess the evolution of student perceptions.

The quantitative component (RQ1–RQ3) is based on survey data collected from these two waves. The qualitative component (RQ4) follows an explanatory sequential approach, in which archived administrative data (information technology help-desk tickets) from the same periods were analyzed to provide rich, contextual examples for the quantitative findings (Creswell & Clark, 2017).

The research was conducted at a large, comprehensive public university in Romania, a member state of the European Union. The university has over 20,000 students and has utilized the Moodle LMS since 2007. During the pandemic, LMS usage became mandatory and universal, and it remains a central component of the university's strategy, in line with the European Union's 2021–2027 vision (European Union, 2021). Within this institutional setting, the university information technology department actively works to mitigate technostress and enhance user satisfaction through several key measures:

- high availability: Continuous LMS accessibility (24/7/365) is ensured to provide reliable access for all students.
- enhanced performance: Ongoing infrastructure improvements—including increased processing power, expanded communication capacity, and component redundancy—ensure a smooth user experience.
- centralized support: A dedicated ticketing system, staffed by experienced information technology specialists, facilitates efficient issue reporting and resolution, with all tickets archived for review.
- user documentation: Customized, LMS-specific guides and resources are provided to help students with common tasks.

Additional features of the e-learning ecosystem include mobile access (Android, iOS), single sign-on, e-mail and video conferencing integration, and peer support platforms. This rich technological environment provides the backdrop for the present investigation. However, it is important to note that, although students generally possess personal computing devices, the quality of their individual internet access varies.

Participants and Procedure

In the quantitative study, the sample was non-random and consisted of self-selected university students, of whom 62.2% were women and 53.7% were from SSHA. Women were predominantly enrolled in SSHA programs (69.9%), whereas men (72.8%) were more often in STEM programs ($\chi = 288.62$, $p < .001$). During the first mandatory online learning period (2020), 662 students (42.3%) participated, while 848 students participated in the following period (2023). All participants in the 2023 subsample had prior online learning experience, including freshmen who used this learning in high school and during the pandemic.

Participants were recruited via institutional e-mail invitations containing an anonymous link to a survey hosted on the open-source LimeSurvey platform, with reminders sent two weeks after the initial invitation. The full questionnaire completion rate was 50.8% in 2020 and 38.1% in 2023 among those who accessed the link. In total, 1,493 participants completed the full questionnaire, of whom 98.4% represented digital natives—that is students born after 1980. Thus, only those digital natives were selected for this study.

The qualitative sample consisted of 358 anonymized help-desk messages sent by students to the ICT department via the university's ticketing application during 2020 and 2023. These messages were directed to the staff responsible for the e-learning platform and BigBlueButton conferencing tool, either by student request or the information technology dispatcher. The data were extracted from archived student tickets without prior selection and related to LMS and the BigBlueButton tool. Institutional consent was obtained to extract and analyze the messages.

Instruments

The first two inventories were translated from English, while the latter were developed by one of the authors of this article. The introductory page of the questionnaire outlined the study's objectives, guaranteed voluntary participation and data anonymity, and informed participants of their right to withdraw at any time.

The Technostress Creators (TC) Scale has 23 items and demonstrates good internal consistency, with a Cronbach's alpha coefficient (CA) equal to .82 for the entire scale. The reliability coefficients for the subscales are as follows (Tarafdar et al., 2007): techno-overload (five items, CA = .90), technoinvasion (four items, CA = .89), technocomplexity (five items, CA = .88), technoinsecurity (five items, CA = .80), technouncertainty (four items, CA = .83).

The Technostress Inhibitors Scale (TI), developed by Ragu-Nathan et al. (2008), has 14 items and demonstrates strong internal consistency, with a CA of .89 for the overall scale. The items are grouped into the three subscales: (1) literacy facilitation (five items, CA = .80); (2) technical support provision (four items, CA = .90); and (3) involvement facilitation (four items, CA = .74).

The items of both scales were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) and were adapted to the research context by comprising the term "university/school."

The Use of E-Learning Platforms Facilities Scale, developed by one of the authors of this article, measures students' use of platform applications through nine items rated on a five-point scale ranging from 1 (almost never) to 5 (almost all the time). The scale demonstrated acceptable internal consistency (CA = .76). The mentioned facilities included chat, forum, conference/videoconference, self-evaluation, sharing materials with colleagues, browsing materials posted by teachers, solving and uploading projects or homework, receiving personalized feedback, and communicating with teachers outside teaching hours.

Satisfaction With Current Use of the E-Learning Platform was measured using a single item: How satisfied are you with your platform usage in the last month? Responses were measured on a 10-point scale ranging from 1 (extremely dissatisfied) to 10 (completely satisfied).

Higher scores on all variables mean greater levels of the variable measured. Sociodemographic information was collected regarding participants' gender, age, and field of study.

Procedure

Data analysis was performed using IBM SPSS 23.0 and SmartPLS v3. To address RQ1 and RQ2, a series of 2x2 factorial ANOVAs were conducted to examine differences based on the independent variables—research year (2020 versus 2023), gender (women versus men), and field of study (SSHA versus STEM)—and their interaction effects on LMS use, satisfaction, technostress creators, and technostress inhibitors. Where significant interactions were found, simple main effects and pairwise comparisons were performed.

Effect sizes (η^2) were categorized as small ($0.01 \leq \eta^2 < 0.06$), medium ($0.06 \leq \eta^2 < 0.14$), and large (> 0.14) (Perugini et al., 2018), with values below 0.01 deemed negligible. When the assumptions of normality and equal variances were violated, the Welch test (W) was applied (Delacre et al., 2019).

To address RQ3, predictors of satisfaction and LMS use were identified through simple and multiple hierarchical regression analyses. The mediation analyses were conducted using SmartPLS v3. Technostress creators and technostress inhibitors were analyzed both individually and as aggregated constructs.

Qualitative data from the help-desk tickets (RQ4) were analyzed using thematic analysis. Two trained coders independently categorized the messages into emergent themes, after which frequencies and percentages for each category were computed to identify the most common student issues. Each category was illustrated with examples of significance units, identified by the gender of the respondents and the year the message was sent.

Common Method Bias

Given that data for both predictor and criterion variables were collected from a single source using self-report measures, several ways were introduced to control for common method bias, as recommended by Podsakoff et al. (2012). First, a number of procedural ways were incorporated into the survey design:

- psychological separation: To reduce participants' emphasis of relationships between constructs, the items measuring technostress creators (predictors), technoinhibitors (mediators), and satisfaction (outcome) were placed in distinct sections of the questionnaire.
- anonymity and confidentiality: The introduction to the survey explicitly guaranteed participants' anonymity and confidentiality of their data. It also emphasized that there were no "right" or "wrong" answers, intending to reduce social desirability bias and encourage more honest responses.
- item clarity: All scale items were reviewed for clarity, simplicity, and conciseness to minimize any potential for item ambiguity.

Second, the study conducted two recommended post hoc statistical tests:

1. Harman's single-factor test: An unrotated factor analysis was performed on all relevant scale items. The results indicated that the first factor accounted for only 22.5% of the total variance. As this value is well below the commonly accepted 50% threshold, it suggests that no single factor is responsible for the majority of the variance in the data.
2. full collinearity assessment: Following the approach recommended by Kock (2015), variance inflation factors were examined for all latent variables in the model. These values were below the conservative threshold of 3.3, indicating that multicollinearity is not a significant issue among the constructs.

As the results indicated that common method bias was not a problem in the data, no further remedies were necessary.

RESULTS

First, the validity and reliability of the instruments are presented, followed by descriptive statistics. Then, the study hypotheses were tested.

Validity and Reliability of the Tools

The validity and reliability of the measurement scales were calculated using PLS-SEM. Composite reliability values for each construct ranged from 0.84 to 0.93, and CA coefficients were at least 0.74, demonstrating acceptable values (see Appendix A). The average variance extracted (AVE) scores were at last 0.53, showing that measurement scales had good convergent validity of each construct. All indicator loadings for reflective measures were above 0.653, further confirming adequate convergent validity. Discriminant validity was assessed using the heterotrait-monotrait ratio, with all values falling below the threshold of 0.90, indicating established discriminant validity between reflective constructs. The Use of E-Learning Facilities construct was treated as a formative construct, with its sub-dimensions considered second-order formative and non-interchangeable factors, for which CR and AVE are not applicable. Detailed reliability and validity metrics are presented in Appendix A.

Descriptive Statistics and Correlations

The means and standard deviations are reported in Table 1. The identified correlations were as expected: the technostress creators and inhibitors were negatively associated with each other; the technostress creators and inhibitors showed negative correlations, whereas technostress inhibitors showed positive correlations with LMS use and satisfaction in both periods. An exception was technouncertainty, which had smaller and/or non-significant associations with learning outcomes compared to other technostress creators (see Table 1). The significant correlation values suggest that the regression models would produce significant effects.

Table 1. Means, Standard Deviations, and Correlations of the Investigated Variables for the Two Years of Research

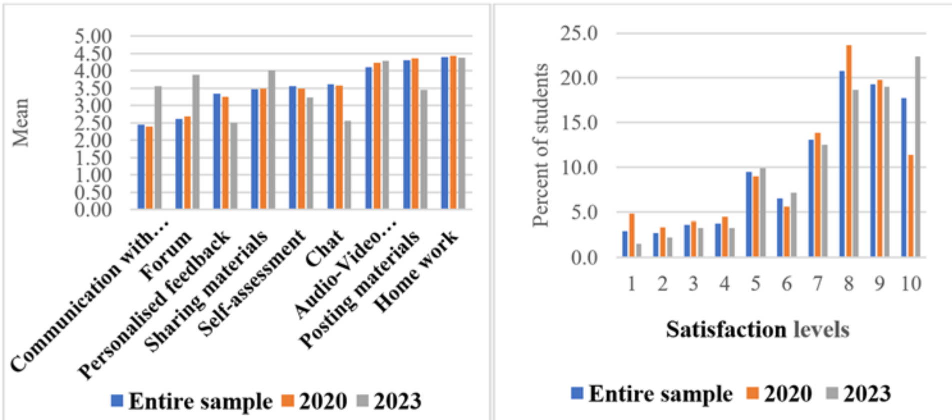
Variables 2020/2023	1	2	3	4	5	6	7	8	9	10	11	12
	2020 – During the first exposure to mandatory online learning											
Mean	6.98	31.9	3.37	3.36	2.46	2.68	2.70	14.56	2.97	3.27	2.69	8.93
SD	2.5	6.3	.96	1.1	.95	.91	.76	3.7	.8	.7	.08	1.9
1. Satisfaction	–	.45**	-.32**	-.26**	-.42**	-.42**	-.16**	-.41**	.39**	.24**	.30**	.37**
2. Use of LMS	.45 **	–	-.13**	-.14**	-.25**	-.19**	-.03	-.20**	.38**	.29**	.32**	.40**
3. T. Overload	-.43**	-.25**	–	.77**	.56**	.60**	.29**	.84**	-.31**	-.22**	-.23**	-.30**
4. T. Invasion	-.39**	-.25**	.76**	–	.48**	.53**	.27**	.81**	-.31**	-.23**	-.27**	-.33**
5. T. Complexity	-.40**	-.25**	.54**	.52**	–	.72**	.45**	.82**	-.30**	-.30**	-.20**	-.32**
6. T. Insecurity	-.41**	-.26**	.57**	.53**	.75**	–	.42**	.84**	-.33**	-.29**	-.24**	-.34**
7. T. Uncertainty	-.10**	-.01	.30**	.25**	.42**	.42**	–	.59**	-.02	-.03	.04	-.01
8. Overall T. Stress Creators	-.45**	-.27**	.84**	.82**	.81**	.82**	.57**	–	-.34**	-.28**	-.25**	-.35**
9. T. Literacy Facilitation	.36**	.37**	-.31**	-.32**	-.18**	-.21**	.13**	.25**	–	.59**	.63**	.89**
10. T. Technical Support	.31**	.31**	-.33**	-.32**	-.20**	-.23**	.01	-.29**	.65**	–	.43**	.79**
11. T. Involvement Facilitation	.31**	.36**	-.28**	-.28**	-.15**	-.18**	.17**	-.20**	.61**	.47**	–	.81**
12. Overall T. Stress Inhibitors	.39**	.41**	-.36**	-.36**	-.21**	-.24**	.13**	-.29**	.89**	.83**	.81**	–
Mean	*7.53*	*31.9*	*2.5*	*2.53*	*2.05*	*2.21*	*2.47*	*11.8*	*3.15*	*3.39*	*2.8*	*9.3*
SD	*2.3*	*6.0*	*.99*	*1.1*	*.81*	*.83*	*.78*	*3.5*	*.8*	*.8*	*.8*	*2.0*

2023 – After familiarization with online learning

Note. LMS = learning management system; T = techno; SD = standard deviation. ** Correlation is significant at the 0.01 level (2-tailed).

In terms of e-platform usage, Figure 2 (left) illustrates the varying degrees to which participants utilized different LMS facilities. The overall mean satisfaction with LMS across the entire sample was 7.32 (on a 10-point scale), with a median of 8.00. As shown in Figure 2 (right), 13.9% of respondents reported satisfaction levels within the bottom three categories, while 45.4% chose the top three levels. Detailed means and standard deviations are provided in Appendix B.

Figure 2. Platform Facilities Used by Students (Left) and Distribution of LMS Satisfaction Levels (Right)



Note. Data regard the entire sample and the two time points of research.

Testing the Hypotheses

To test hypotheses H1–H4, two-way ANOVA was performed. The F or Welch test, p values, and partial η^2 are displayed in Appendix C.

- H1 (LMS use): As shown in the left panel of Figure 3, a significant interaction effect between year and gender was found for LMS use ($p = .02$, $\eta p^2 < .01$). While women's usage remained stable, men significantly increased their LMS use from 2020 to 2023 ($F = 3.86$, $p = .05$), effectively closing the gender gap present in the initial period. Thus, H1.3 was supported for gender, whereas H1.2 (predicting stable use for all) was not. As hypothesized in H1.1, women used LMS more than men in 2020, and SSHA students used it more than STEM students across both years ($p < .001$).
- H2 (satisfaction): Supporting H2.2, overall satisfaction with LMS was significantly higher in 2023 than in 2020 ($F = 29.79$, $p < .001$). Again, a significant interaction was present: the increase in satisfaction was more pronounced for men ($F = 27.79$, $p < .001$) than for women ($F = 4.29$, $p = .038$). This finding supports H2.3 (for gender interaction) and explains the convergence in satisfaction levels by 2023. Partially supporting H2.1, women were more satisfied than men in 2020; however, this difference disappeared by 2023. Hypotheses H2.3b and H2.3b, regarding the interaction effect between research year and field of study, were not validated.
- H3 (technostress creators): In strong support of H3.2, students perceived significantly higher levels of overall technostress in 2020 compared to 2023, with a medium effect size ($\eta p^2 = .11$). This difference was primarily driven by reductions in techno-overload ($\eta p^2 = .13$) and technoinvasion ($\eta p^2 = .11$). Partially supporting H3.1, women consistently reported slightly higher levels of technostress creators than men. No significant interaction effects were found for this variable (H3.3).
- H4 (technoinhibitors): As hypothesized in H4.2, students evaluated institutional resources (technoinhibitors) significantly more favorably in 2023 than in 2020 ($\eta p^2 = .01$). In line with H4.1, women and SSHA students rated these support resources more positively than their male and STEM counterparts across both years, though the effect sizes were small. No significant interaction effects were found for inhibitor perceptions (H4.3).

The hypotheses for the predictive model were tested using a series of simple and hierarchical multiple regressions.

- H5.1 (effect of inhibitors on creators): To test the direct effect of resources on demands, a simple regression was conducted. Technoinhibitors were found to be a significant negative predictor of technostress creators. This relationship held for the entire sample ($\beta = -.32$, $p < .001$) and was consistent across both 2020 ($\beta = -.35$, $p < .001$) and 2023 ($\beta = -.29$, $p < .001$), as well as for both women ($\beta = -.37$, $p < .001$) and men ($\beta = -.28$, $p < .001$). Therefore, H5.1 is supported.
- H5.2–H5.4 (predicting LMS use and satisfaction): To test the core predictive relationships in the model, hierarchical regressions were conducted separately for 2020 and 2023 (see Table 2).

Table 2. Hierarchical Regressions with Use of E-Learning Platform Facilities and Satisfaction as Dependent Variables: Comparison of the Two Years of Study (H5.2–H5.4)

Predictors	First exposure to mandatory online learning (2020)						After familiarization with online learning (2023)					
	Use of e-learning platform facilities (R2 = .28, F = 38.85, p < .001)			Satisfaction with e-learning platform (R2 = .37, F = 60.39, p < .001)			Use of e-learning platform facilities (R2 = .27, F = 101.31, p < .001)			Satisfaction with e-learning platform (R2 =. 35, F = 92.29 p < .001)		
Model	Coefficients		t	Coefficients		t	Coefficients		t	Coefficients		t
	b	Beta		b	Beta		b	Beta		b	Beta	
(Constant)	20.7		11.12***	5.5		7.99***	18.3	-	22.22***	5.2	-	10.53***
Gender (1-W, 2-M)	-1.02	-.08	-2.14*	-.72	-.14	-4.17***	-	-	-	-	-	-
T. Overload	.65	.10	2.38*	-	-	-	-	-	-	-.39	-.17	-4.84***
T. Complexity	-.66	-.10	-2.31*	-.45	-.17	-3.7***	-	-	-	-.39	-.14	-3.28***
T. Insecurity	-	-	-	-.55	-.20	-4.32***	-	-	-	-.27	-.01	-2.23*
T. Literacy facilitation	1.29	.17	3.7***	.415	.14	3.86***	1.06	.15	3.82***	.44	.16	5.19***
T. Support	-	-	-	-.26	-.08	-1.9a	-	-	-	-	-	-
T. Involvement facilitation	.92	.11	2.58**	-	-	-	1.23	.16	4.35***	-	-	-
Use of LMS	-	-	-	.12	.30	8.43***	-	-	-	.11	.28	9.294***
Satisfaction	.83	.33	8.03***	-	-	-	.91	.34	10.74***	-	-	-

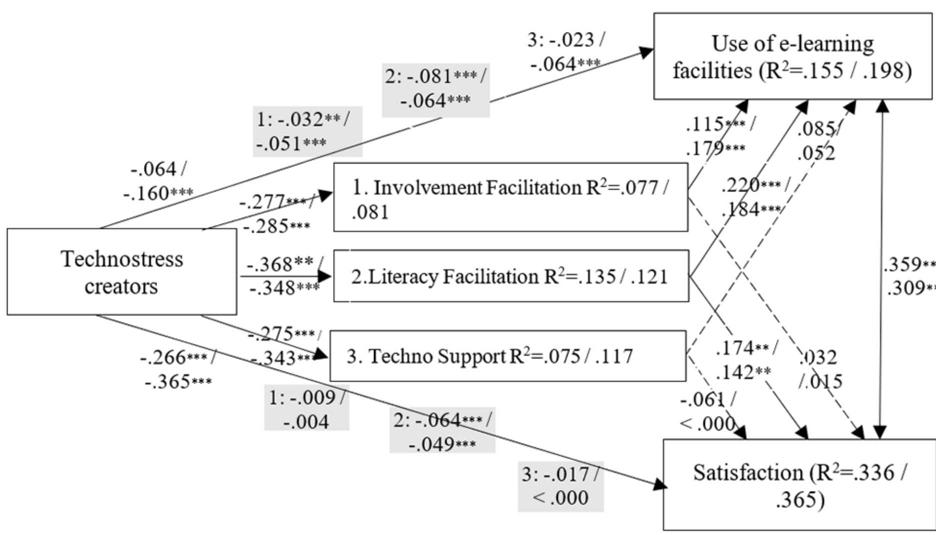
Note. LMS = learning management system; T = techno. Gray cell-variables not entering the models; cells with – = variables not predicting the dependent variables significantly and not entering the models. ***. significance at the 0.001 level. ** significance at the 0.01 level. * significance at the 0.05 level, a marginal significance p = .058).

- H5.2 and H5.3 (evolving predictors of use and satisfaction): The influence of technostress creators and inhibitors changed significantly over time. In 2020 (initial exposure), during the initial high-stress period, both technostress creators and inhibitors significantly predicted outcomes. Surprisingly, techno-overload positively predicted LMS use ($\beta = .10$, $p < .05$). Most notably, technical support had a marginal, but negative relationship with satisfaction ($\beta = -.08$, $p = .058$). By 2023 (familiarization), the predictive model had shifted: the effects of most technostress creators on both LMS use and satisfaction had diminished and were no longer significant. However, literacy facilitation remained a strong and significant positive predictor of both LMS use ($\beta = .15$, $p < .001$) and satisfaction ($\beta = .16$, $p < .001$).

Given this complex and evolving pattern of results, H5.2 and H5.3 are partially validated. Some creators and inhibitors predicted use and satisfaction as expected; however, the effects changed over time.

- H5.4 (mutual prediction of LMS use and satisfaction): As hypothesized, the reciprocal relationship between e-platform use and satisfaction was strongly supported in both years. In the 2020 model, satisfaction was a powerful predictor of LMS use ($\beta = .33$, $p < .001$), and use was a powerful predictor of satisfaction ($\beta = .30$, $p < .001$). This dynamic remained robust in 2023, confirming the reinforcing loop from the D&M model. H5.4 is supported.
- H5.5 (buffering hypothesis): To test this hypothesis, a parallel mediation analysis was conducted. The validated model, showing the direct and indirect effects for both the 2020 and 2023 cohorts, is presented in Figure 3. Direct effects of technostress creators on LMS use ($\beta = –.064$, $p < .178$ in 2020 and $\beta = –.160$, $p < 001$ in 2023) and on satisfaction ($\beta = –.266$, $p < .001$ in 2020 and $–.324$, $p < .001$ in 2023) were negative. In contrast, technostress inhibitors positively affected both LMS use and satisfaction, though not always significantly. Mediation analysis revealed that all technoinhibitor dimensions partially mediated the relationship between technostress creators and LMS use, supporting the hypothesis. The relationship between technostress creators and satisfaction was partially mediated by individual technoinhibitor dimensions, with only literacy facilitation serving as a partial mediator for both LMS use and satisfaction across both years. After students gained familiarity with online learning, the direct effect of technostress creators on LMS use remained negative, but its indirect specific effects significantly decreased through all inhibitors.

Figure 3. Parallel Mediation Model of the Effects of Technostress Creators on Outcomes Through Three Inhibitors Across Two Waves (H5.4)



*Note. The model displays standardized path coefficients (β). Values are presented as 2020 subsample/2023 subsample. Solid lines indicate significant paths; dashed lines indicate non-significant paths. Shaded boxes represent the specific indirect (mediated) effect for each inhibitor on the outcome variables. *p < .01. ***p < .001.*

Serial mediation analyses were conducted to explore the distinct pathways through which technoinhibitors influence satisfaction, with LMS use serving as the second step in the path. The results confirmed that the three inhibitors are not interchangeable. Literacy facilitation emerged as the most robust mediator, significantly buffering the effect of technostress on satisfaction—both directly and indirectly through its positive influence on LMS use. In contrast, involvement facilitation mediated satisfaction only indirectly through LMS use, as its direct path was not significant. Technical support failed to function as a significant direct mediator, showing its ineffectiveness in directly buffering negative impact of technostress on satisfaction.

Table 3. Single and Serial Mediations from Technostress Creators to Satisfaction

Mediation chains	**Entire sample**		**First exposure to mandatory online learning 2020**		**After familiarization with online learning 2023**	
	Path values	**p**	**Path values**	**p**	**Path values**	**p**
Technostress creators -> *TI literacy facilitation* -> satisfaction	–0.051	0.001	–.064	.005	–.049	.003
Technostress creators -> *TI literacy facilitation* -> use of e-learning -> satisfaction	–0.019	0.001	–.029	.001	–.020	.002
Technostress creators -> *TI involvement facilitation* -> satisfaction	–0.007	0.360	–.009	.508	–.004	.685
Technostress creators -> *TI involvement facilitation* -> use of e-learning -> satisfaction	–0.014	0.001	–.011	.045	–.016	< .001
Technostress creators -> *TI techno support* -> satisfaction	0.007	0.431	.017	.196	< .001	> 0.99
Technostress creators -> *TI techno support* -> use of e-learning -> satisfaction	–0.009	0.016	–.008	.104	–.005	.248

Note. TI = technoinhibitors

Qualitative Study Results

The help-desk ticket topics were grouped into four categories, as displayed in Table 4. In the first year of research (2020), the number of messages was higher, 89.1% of the total, compared to the second year (2023). Most messages in both periods of research were submitted by women (58.1%). To provide context, illustrative examples are identified by student gender (W = women; M = men) and the year in which the message was sent (2020 or 2023).

Table 4. Frequency and Percentage for the Categories of Help Messages Received by the Information Technology Department (RQ4)

Categories	Frequencies (%)				Total (%)
	Women		Men		
	2020	2023	2020	2023	
1. Software configuration deficiencies	92 (25.7)	5 (1.4)	84 (23.5)	7 (1.95)	188 (52.5)
2. Deficiencies in connection, student equipment, or other misunderstanding	45 (12.6)	7 (1.95)	21 (5.86)	6 (1.67)	79 (22.07)
3. Subject or content insufficiently formulated or lacking detail	24 (6.7)	5 (1.4)	16 (4.47)	3 (0.8)	48 (13.4)
4. Bugs with the conference application	18 (5.03)	2 (0.28)	6 (1.67)	-	26 (7.26)
5. Access to past courses	8(2.2)	2 (0.55)	5 (1.4)	2 (0.56)	17 (4.7)
Total	187 (52.23)	21 (5.86)	132 (36.87)	18 (5.03)	358

Examples of message units by category:

- C1. Software configuration deficiencies: “I can’t log in to the e-learning platform” (M, 2023). “Courses not assigned” (W, 2020). “Non-validation of data when registering on e-learning” (M, 2020). “I don’t have access to courses” (W, 2023). “Email account suspended” (W, 2020). “Invalid authentication” (M, 2020). “404 error” (M, 2023). “Add new button missing” (W, 2020).
- C2. Deficiencies in connection, student equipment, or other misunderstanding: “Problems loading presentations” (W, 2020). “Microphone problems” (W, 2020). “I can’t access the e-learning platform from the laptop” (M, 2020). “It doesn’t load the page to me” (W, 2023). “No course is visible in the application” (W, 2020). “Problems. I can’t see the teachers” (W, 2020). “I can’t access the courses with my mobile phone” (W, 2020).
- C3. Subject or content insufficiently formulated or lacking detail: “e-Learning platform” (W, 2020). “Platform problem!” (W, 2020). “I cannot carry out my activities on e-learning!” (W, 2020). “The platform does not work!” (M, 2020). “I cannot do anything on e-learning!” (W, 2023). “BBB problem” (W, 2020).
- C4. Bugs with the conference application: “I can’t access the conferences” (M, 2020). “Automatic disconnection from the BBB conference” (W, 2023).
- C5. Access to past courses: “How do I access the platform with the courses of the last semester?” (W, 2023). “How do I get to the archive 2017–2018?” (M, 2023).

To provide an overview, Table 5 summarizes the research hypotheses and their status after their testing.

Table 5. Status of Hypotheses After Testing

Hypothesis	Supported?
H1.1: Gender and field of study have a significant effect on LMS usage, with (a) women and (b) SSHA students using LMS more frequently than men and STEM students (RQ1).	Supported. Group differences were significant as predicted.
H1.2: Students use LMS at similar levels during both the initial mandatory online learning phase and the subsequent period of familiarization (RQ1).	Not supported. A significant interaction effect showed that men's usage increased, contradicting overall stability.
H1.3: There is a statistical interaction between year of research and (a) gender or (b) field of study in LMS use (RQ1).	Partially supported. The interaction was significant for Year × Gender, but not for Year × Field of Study.
H2.1: Gender and field of study significantly impact LMS satisfaction, with (a) women and (b) SSHA students reporting higher satisfaction than men and STEM students, respectively (RQ1).	Partially supported. The predicted differences were only present in one of the two years.
H2.2: The year of research significantly affects satisfaction, with students reporting lower satisfaction during the initial mandatory e-learning phase compared to the period of familiarization (RQ1).	Supported. Satisfaction was significantly higher in 2023 than in 2020.
H2.3: There is statistical interaction between year of research and (a) gender or (b) field of study in satisfaction (RQ1).	Partially supported. The interaction was significant for Year × Gender, but not for Year × Field of Study.
H3.1: Gender and field of study significantly influence perceptions of technostress creators, with (a) women and (b) SSHA students perceiving higher levels of technostress creators compared to men and STEM students (RQ2).	Partially supported. The predicted group differences were found to be statistically significant.
H3.2: The year of research has a significant impact on the perception of technostress creators, with students perceiving higher technostress during the initial mandatory e-learning phase than after becoming familiarized with the environment (RQ2).	Supported. Technostress levels were significantly lower in 2023.
H3.3: There is statistical interaction between year of research and (a) gender or (b) field of study in the perception of technostress creators (RQ2).	Not supported. No significant interaction effects were found.
H4.1: Gender and field of study significantly influence perception of technoinhibitors, with (a) women and (b) SSHA students expected to have a more favorable appraisal of technostress inhibitors compared to men and STEM students (RQ2).	Supported. The predicted group differences were statistically significant.
H4.2: The year of research has a significant effect on the perception of technoinhibitors, with students appraising them more favorably after extended exposure to compulsory online learning compared to the initial period (RQ2).	Supported. Inhibitors were valued significantly more in 2023.
H4.3: There is significant interaction between the year of research and (a) gender or (b) field of study in the perception of technostress inhibitors (RQ2).	Not supported. No significant interaction effects were found.
H5.1: Technostress inhibitors are expected to negatively predict technostress creators (RQ3).	Supported. A consistent, significant negative relationship was found across all groups and time periods.
H5.2: LMS use is predicted (a) negatively by technostress creators and (b) positively by technoinhibitors (RQ3).	Partially supported. The effects were context-dependent and varied by year. In fact, some were counterintuitive (e.g., techno-overload).

continued on following page

Table 5. Continued

Hypothesis	Supported?
H5.3: Satisfaction is predicted (a) negatively by technostress creators and (b) positively by technoinhibitors (RQ3).	Partially supported. The effects were context-dependent and varied by year. In fact, some were counterintuitive (e.g., technical support).
H5.4: LMS use and satisfaction mutually predict each other (RQ3).	Supported. A strong, reciprocal, and positive relationship was confirmed in both years.
H5.5: Technostress inhibitors mediate relationships between technostress creators and (a) LMS use and (b) satisfaction (RQ3).	Partially supported. Mediation was confirmed. However, the strength and paths of the effects varied significantly by inhibitor type.

DISCUSSION

This research, which addresses the dark side of technologies and higher education's adaptation to the digital age, investigates the role of technoinhibitors in mitigating the negative impact of technostress on LMS usage and student satisfaction. User interactions with LMS are examined within an organizational context, comparing initial mandatory use and subsequent use. Most of the relationships of the proposed model are supported: there is a reciprocal relation between satisfaction and LMS use, and the negative effects of technostress on satisfaction are reduced by the combined efforts of technoinhibitors and LMS usage, particularly through the influence of literacy facilitation. Although the participants are all digital natives, they experienced more technostress in the first year and adapted better in the second year. Their evolving experience may be attributed to LMS familiarity, improved ICT skills or greater awareness of information technology support, validating the idea that negative aspects of technology can be transformed into positive outcomes under specific conditions. These results reinforce the importance of organizational intervention to support digital learning.

Evolution of LMS Use and Satisfaction

Consistent with the mandatory character of the e-learning platform, this study's findings show that overall LMS usage remained stable across the two study periods, aligning with research indicating a continued e-learning adoption in the post-pandemic era (e.g., Confini et al., 2022). However, beneath this stability, the analysis reveals a more subtle story of student adaptation, particularly regarding the evolution of gendered patterns and satisfaction.

LMS use presents a dynamic evolution of gendered patterns. In 2020, during the initial rapid transition to online learning, women and SSHA students reported higher levels of LMS usage than their male and STEM counterparts. While comprehensive LMS features utilization validates initial positive digital native responses, the period was marked by technical challenges, as confirmed in prior research (e.g., Dhawan, 2020). The qualitative data from help-desk tickets provides rich context for the frustrations of this initial period. Student requests frequently reported issues such as incorrect credentials, expired passwords, enrollment errors, server fluctuations, and device incompatibility. The high emotional load of this period, evidenced by exclamatory statements, points to a stressful environment in which every login attempt could become a struggle or disappointment.

The initially lower LMS usage among men, a group often perceived as more familiar with technology, was unexpected. A plausible explanation is a difference in engagement styles within a home-learning context and the ways they felt external pressures. However, by 2023, men significantly increased their LMS usage, eliminating the initial gender gap. This shift aligns with the technology acceptance model, suggesting that as LMS became institutionalized, its perceived usefulness (Marikyan

& Papagiannidis, 2025; Venkatesh et al., 2003) and the subjective norms from peers and faculty (Guo et al., 2024), amplified their importance.

Satisfaction with LMS showed a clear and positive evolution across all groups from 2020 to 2023. This overall improvement can be attributed to the reduction in technostress, increased student familiarity with the platform, and likely enhancements in system usability and information technology service quality. However, the dynamics within this trend are more complex. An intriguing finding from 2020 is that women reported higher satisfaction than men, despite also experiencing significantly higher levels of technostress. The contradictory finding suggests that women may have changed their appraisal of sources of stress and adapted their behaviors accordingly. By 2023, the dynamic had shifted. While satisfaction rose for both genders, the increase was most pronounced among male students, which eliminated the gender gap observed in 2020. This convergence suggests that as an individual interacts more with the platform and achieves greater mastery of its knowledge, their satisfaction increases. The evolution underscores the strong reciprocal relationship between usage and satisfaction that was proposed in this model. These observed group variations are consistent with research highlighting the heterogeneity of skills and attitudes even among "digital native" students (Nastjuk et al., 2023; Upadhyaya & Vrinda, 2022).

Dynamic of Technostressors and Technoinhibitors

The dynamics of technostress creators and inhibitors are crucial to understanding the student adaptation process. As expected, all technostressors were perceived more intensely in 2020, as a consequence of the abrupt transition to mandatory online learning and the broader environmental stress of the COVID-19 pandemic. These differences are important from a practical point of view. The medium to high values of partial η^2 for techno-overload, technoinvasion, and general technogenic stress show that the year of the research explains a large part of the variance. The subsequent reduction in perceived stress by 2023 across the entire sample likely reflects students' increased coping experience and the stabilizing support from the university. Across both periods, women reported higher levels of technostress than men, aligning with literature citing factors such as emotional sensitivity (Korlat et al., 2021) and cultural context characterized by high power distance and masculinity, which can exacerbate women's perceived inability to use computers and LMS platforms (Hofstede et al., 2010).

A key novel finding of this study is that students evaluated institutional resources (technoinhibitors) more favorably in 2023 than in 2020, even as their direct need for support, measured by the number of help-desk tickets, decreased. This presents a paradox: support was more valued when it seemed to be less needed. The explanation could lie in the distinction between the frequency of requesting help and the quality of the experience. In 2020, the higher volume of support tickets reflected a period when students were forced to request support for basic LMS functionalities. Such experiences were likely associated with feelings of incompetence and a lower appraisal of information technology services, especially technosupport. In the subsequent period, students requested formal help less frequently but appraised organizational resources more favorably. This shift suggests that information technology support became a comforting safety net rather than a frustrating necessity. However, it is also possible that the quality of services offered by the department increased between the two periods.

This interpretation is further enriched by gender dynamics. The finding that women evaluated inhibitors more positively is consistent with research showing that they are more socially oriented and willing to seek help (Koc & Liu, 2016; Verbree et al., 2023), particularly when experiencing higher levels of stress (Asensio-Martínez et al., 2023). In contrast, men's reluctance to seek help, potentially due to a desire to appear competent and self-reliant, may explain their lower evaluation of these resources (Koc & Liu, 2016; Lazarus & Folkman, 1984). The qualitative data supports this finding, confirming a gender disparity in formal help-seeking behavior that aligns with the quantitative findings. Together, these results suggest that adaptation to educational technology is not immediate—students require time to develop their information technology skills and build positive attitudes toward the demands of online learning.

Predictors and Mediators of LMS Use and Satisfaction

According to the hypothesis model, technostress creators and technoinhibitors influence learning satisfaction and LMS use both independently and interactively. The predictive models explain an acceptable proportion of the variance in student outcomes (usage and satisfaction), with R^2 values ranging from 27% to 37%. More importantly, the analysis reveals a dynamic picture of how technological stressors and institutional support influence student satisfaction, moving beyond simplistic negative or positive evaluations.

Another main finding of the current study is that the facets of stressors do not have a uniformly negative impact. While technocomplexity consistently hinders both platform use and satisfaction, techno-overload shows a positive relationship with LMS use during the initial 2020 transition period. This suggests that, in a mandatory environment with high requirements, overload may have acted as a “challenge stressor.” This distinction resonates with theoretical work on eustress versus distress (Tarafdar et al., 2019) and with technology acceptance models that link perceived usefulness to behavior, even under pressure (Marikyan & Papagiannidis, 2025). The perspective is convergent with the statement that a combination of high challenge job demands and resources lead to work engagement—manifested here as greater LMS use (Ayyagari et al., 2011; Bakker et al., 2023). Complementarily, the positive connection between overload and LMS use in 2020 may be explained by inefficient usage patterns by students with weak initial information technology skills. By 2023, as students became more efficient, this effect disappeared, showing the context-dependent nature of the stressor.

While information technology interventions generally proved beneficial, the study’s findings confirm past studies and reveal another unexpected result. Consistent with pre-pandemic research, technoinhibitors such as literacy facilitation clearly increase both LMS usage and satisfaction (e.g., Al-Fraihat et al., 2020; Machado-Da-Silva et al., 2014). Learning about e-learning empowers stressed students, enhancing their engagement and satisfaction. However, in 2020, increased interaction with technical support was associated with a decrease in satisfaction, contradicting some previous literature (e.g., Saleem et al., 2024). The primary explanation resonates with the social cognitive theory (Bandura, 2001): the act of seeking help can serve as a negative self-signal, confirming an individual’s inability to manage a stressor independently, which may diminish learners’ confidence and sense of control. This psychological explanation is complemented by pragmatic factors. This study’s qualitative analysis reveals that a majority of help-desk tickets were related to software configuration deficiencies, likely contributing to a negative user experience. In contrast, literacy facilitation interventions (e.g., training, guidance) consistently predicted higher use and satisfaction, suggesting that interventions aimed at developing students’ skills are much more beneficial than support that temporarily solves problems.

Ultimately, this study supports the previous negative evaluation of technological stressors and the positive role of inhibitors (Schaufeli & Taris, 2014), while adding that their effects in a real-world learning context, including crisis periods, are more complex. The partial validation of this study’s hypothetical model highlights this complexity, and the results of the mediation analysis reinforce this point of view. Thus, it is shown that technological inhibitors and LMS use form a “protective group” within mandatory e-learning settings.

Limitations and Future Research

The findings of this study should be interpreted in light of several limitations. First, the reliance on a non-random sample from a single university in Romania, which has an imbalance of gender and field of study, limits the generalizability of the findings. Second, the comparative cross-sectional design, while effective for observing changes between independent samples, does not track the same individuals over time. Consequently, the findings represent associations rather than causal pathways, though some causal links may exist. Third, on a measurement level, the use of a single-item measure to assess user satisfaction was a pragmatic choice to reduce participant fatigue; however, it inherently has lower reliability and construct validity than established multi-item scales. Finally, the study did not account for all potential unmeasured confounders, such as individual differences in academic stress or perceived risk from COVID-19, which could increase students' levels of technostress.

The limitations provide a clear roadmap for future inquiry. To address generalizability, future research should employ longitudinal panel designs that track the same students across multiple institutions and diverse cultural contexts. These future studies should adopt validated multi-item satisfaction scales (e.g., from the information systems success model or SERVQUAL) to ensure a more reliable and valid measurement of this key variable. Looking forward to the growing era of AI in education, future research should examine how digital stress is shaped by factors such as students' digital identity and online behavior within these complex ecosystems (Sverdlyka et al., 2022). For instance, studies could leverage intelligent systems and AI-driven analysis of LMS log data to passively measure engagement and identify behavioral markers of stress, leading to the design of intelligent, adaptive interventions that provide real-time support (Fedushko et al., 2022).

Implications and Conclusions

The findings of this two-year research on the use of LMS under technological stress and information technology services support provide insights for specialized literature and organizations, improving the understanding of this topic.

Theoretical Implications

This study's findings offer significant contributions to understand the technostress and technology adoption in mandatory educational settings. First, the research challenges the predominantly negative conceptualization of technostressors by supporting their dual nature and context dependence. These findings suggest that future theoretical models of technostress should effectively include the previous framework (e.g., Bakker et al., 2023; Lazarus & Folkman, 1984; Tarafdar, 2019) to account for both the positive, "challenge-based," pathways through which stress can influence outcomes. This feature is particularly relevant in mandatory and crisis-period contexts, where students must engage with technology to meet learning requirements.

Second, the study extends the JD-R and information systems success models by testing them in a double non-traditional environment: mandatory online learning within the academic environment. The evolving behavior of male students highlights the long-term influence of perceived usefulness (Venkatesh et al., 2003), showing that even with mandatory adoption, utility remains a powerful driver. These results can explain some of the differences observed between research conducted in optional learning environments (before the pandemic) and those in mandatory learning environments (during the pandemic), as well as between research in work and academic environments.

The disaggregated analysis of technostressors and inhibitors provides nuanced explanations for two paradoxical findings: the positive link between techno-overload and LMS usage time in 2020, and the negative relationship between technical support and satisfaction. These insights would be obscured by an aggregate analysis, highlighting the need for more granular, multi-dimensional models in future research.

Practical Implications

Given the potential for obstructive global events or to support the expansion of hybrid learning, the current study offers valuable practical implications that can support preventive and remedial management. The study's findings translate into several evidence-based recommendations for university administrators, information technology managers, and educators aiming to create more effective and supportive digital learning environments.

First, universities should move beyond a "one-size-fits-all" approach and tailor support for different student groups. The common "digital native" label is misleading, as the study's results confirm that students, even of the same generation, have heterogeneous skills and needs. Thus, for women, universities should provide highly visible literacy facilitation resources (e.g., guides, workshops) to build confidence and mitigate strain. For men, interventions should focus on normalizing help-seeking behaviors and clearly communicating the utility and necessity of LMS for academic success to drive engagement. Ignoring these evidence-based differences is unproductive and unfair.

Second, universities should prioritize what works by focusing on literacy facilitation. Not all support has beneficial effects. Thus, universities should focus their resources on efforts that enhance students' core digital skills.

Third, universities should reframe information technology support to focus on empowerment rather than just closing tickets. Support staff should be trained to listen to students' frustrations, avoiding technical jargon and framing solutions in ways that build users' confidence and sense of autonomy.

Fourth, universities should adopt a long-term, evidence-informed perspective. Because adaptation to digital environments takes time, administrators should avoid making hasty decisions about digital learning initiatives based on short-term data. To become more evidence-based, universities can leverage the analytical capabilities of their own LMS platforms—for instance, by analyzing system log data to identify students who struggle to access materials, allowing for timely and targeted interventions. Likewise, policymakers assessing digital education should consider the time needed for students to learn and adapt to LMS use.

Finally, the role of ICT services as a protective factor in stressful online learning, as demonstrated by current qualitative and quantitative data, highlights the need to prioritize high-quality digital environments. Preventive measures should include ensuring that the LMS platform is supported by a robust technological infrastructure, friendly design, and software configurations with minimal deficiencies—all tailored to targeted user needs.

By comparing two distinct student samples—one from the emergency phase of the pandemic (2020) and another from a later period of familiarization (2023)—this mixed-method study addresses a pertinent issue for academic institutions and systems designers. The main result of current research is that student adjustment to mandatory educational technology is a dynamic process: small successes in LMS use boost satisfaction, which then encourages further use. The current findings suggest that while technological demands can create significant stress, targeted organizational interventions can successfully mitigate these negative impacts. LMS successes and positive perceptions that emerged in the second wave of this study emphasize the need for institutions to adopt a persistent and evidence-based approach to digital transformation. The effectiveness of this support, however, is subtle: resources that build students' skills and confidence generate learning success. True integration is achieved gradually, resulting from the long-term interplay between technological systems and thoughtful, user-centered support.

AVAILABILITY OF DATA AND MATERIAL

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

COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

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REFERENCES

Abd Aziz, N. N., Aziz, M. A., & Abd Rahman, N. A. S. (2023). The mediating effects of student satisfaction on technostress–performance expectancy relationship in university students. *Journal of Applied Research in Higher Education*, *15*(1), 113–129. DOI: 10.1108/JARHE-03-2021-0117

Abdous, M. (2019). Influence of satisfaction and preparedness on online students' feelings of anxiety. *The Internet and Higher Education*, *41*(1), 34–44. DOI: 10.1016/j.iheduc.2019.01.001

Al-Fraihat, D., Joy, M., Masa'deh, R., & Sinclair, J. (2020). Evaluating e-learning systems success: An empirical study. *Computers in Human Behavior*, *102*, 67–86. DOI: 10.1016/j.chb.2019.08.004

Al Shamsi, I. R. (2024). Optimizing STEM education via e-Learning: Addressing challenges and strategic planning for graduate employment outcomes. *Emerging Science Journal*, *8*(6), 231–248. DOI: 10.28991/ESJ-2024-SIED1-014

Alshammari, S. H. (2020). The influence of technical support, perceived self-efficacy, and instructional design on students' use of learning management systems. *Turkish Online Journal of Distance Education*, *22*(3), 112–141. DOI: 10.17718/tojde.762034

Asensio-Martínez, A., Aguilar-Latorre, A., Masluk, B., Gascón-Santos, S., Sánchez-Calavera, M. A., & Sánchez-Recio, R. (2023). Social support as a mediator in the relationship between technostress or academic stress and health: Analysis by gender among university students. *Frontiers in Psychology*, *14*, 1236825. DOI: 10.3389/fpsyg.2023.1236825 PMID: 37744603

Ayyagari, R., Grover, V., & Purvis, R. (2011). Technostress: Technological antecedents and implications. *Management Information Systems Quarterly*, *35*(4), 831–858. DOI: 10.2307/41409963

Bakker, A. B., Demerouti, E., & Sanz-Vergel, A. (2023). Job demands-resources theory: Ten years later. *Annual Review of Organizational Psychology and Organizational Behavior*, *10*(1), 25–53. DOI: 10.1146/annurev-orgpsych-120920-053933

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology*, *52*(1), 1–26. DOI: 10.1146/annurev.psych.52.1.1 PMID: 11148297

Berger, M., Schäfer, R., Schmidt, M., Regal, C., & Gimpel, H. (2024). How to prevent technostress at the digital workplace: A Delphi study. *Journal of Business Economics*, *94*(7-8), 1051–1113. DOI: 10.1007/s11573-023-01159-3 PMID: 38625156

Bradley, V. M. (2021). Learning management system (LMS) use with online instruction. *International Journal of Technology in Education*, *4*(1), 68–92. DOI: 10.46328/ijte.36

Butler, D., Leahy, M., Charania, A., Gedara, P. M., Keane, T., Laferrière, T., Nakamura, K., Ueda, H., & Bocconi, S. (2024). Aligning digital educational policies with the new realities of schooling. *Technology. Knowledge and Learning*, *29*(4), 1831–1849. DOI: 10.1007/s10758-024-09776-9

Cahyono, A. E., Herawati, Y. W., & Al Anshory, A. M. (2022). Online teaching by digital native and digital immigrant lecturers of higher education. *International Journal of Innovative Technologies in Social Science*, *4*(36), 1–14. DOI: 10.31435/rsglobal_ijitss/30122022/7934

Cofini, V., Perilli, E., Moretti, A., Bianchini, V., Perazzini, M., Muselli, M., Lanzi, S., Tobia, L., Fabiani, L., & Necozione, S. (2022). E-learning satisfaction, stress, quality of life, and coping: A cross-sectional study in Italian university students a year after the COVID-19 pandemic began. *International Journal of Environmental Research and Public Health*, *19*(13), 8214. DOI: 10.3390/ijerph19138214 PMID: 35805872

Creswell, J. W., & Clark, V. L. P. (2017). *Designing and conducting mixed methods research*. Sage Publications.

Day, L., Colonnese, F., Gasparotti, A., Batura, O., Melstveit, M., Olausson, N., Hammonds, W., Hallissy, M., & Looney, J. (2023). *Digital education content in the EU: State of play and policy options: Final report*. Publications Office of the European Union. https://data.europa.eu/doi/10.2766/682645

Delacre, M., Leys, C., Mora, Y. L., & Lakens, D. (2019). Taking parametric assumptions seriously: Arguments for the use of Welch's F-test instead of the classical F-test in one-way ANOVA. *Revue Internationale de Psychologie Sociale*, *32*(1), 1–12. DOI: 10.5334/irsp.198

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, *19*(4), 9–30. DOI: 10.1080/07421222.2003.11045748

Dhawan, S. (2020). Online learning: A panacea in the time of COVID-19 crisis. *Journal of Educational Technology Systems*, *49*(1), 5–22. DOI: 10.1177/0047239520934018

European Union. (2021). *Digital education action plan (2021–2027).* https://education.ec.europa.eu/focus-topics/digital-education/action-plan

Faize, F. A., & Nawaz, M. (2020). Evaluation and improvement of students' satisfaction in online learning during COVID-19. *Open Praxis*, *12*(4), 495–507. DOI: 10.5944/openpraxis.12.4.1153

Fedushko, S., Ustyianovych, T., & Syerov, Y. (2022). Intelligent academic specialties selection in higher education for Ukrainian entrants: A recommendation system. *Journal of Intelligence*, *10*(2), 32. DOI: 10.3390/jintelligence10020032 PMID: 35736004

Guo, H., Ye, Y., Lin, Y. C., Khan, A., Chen, S. C., & Liou, J. H. (2024). Evaluating the determinants on students' switching intentions towards distance learning: An extension of the theory of planned behavior. *Cogent Social Sciences*, *10*(1), 2356721. Advance online publication. DOI: 10.1080/23311886.2024.2356721

Hadad, S. (2025). Factors influencing student help-seeking behavior during crisis: A mixed-method analysis in higher education. *Studies in Higher Education*, 1–19. DOI: 10.1080/03075079.2025.2468842

Hang, Y., Hussain, G., Amin, A., & Abdullah, M. I. (2022). The moderating effects of technostress inhibitors on techno-stressors and employee's well-being. *Frontiers in Psychology*, *12*, 821446. DOI: 10.3389/fpsyg.2021.821446 PMID: 35082738

Hofstede, G., Hofstede, G. J., & Minkov, M. (2010). *Cultures and organizations: Software of the mind*. McGraw-Hill.

Ionescu, C. G., Chendea, A., & Licu, M. (2023). Is satisfaction with online learning related to depression, anxiety, and insomnia symptoms? A cross-sectional study on medical undergraduates in Romania. *European Journal of Investigation in Health, Psychology and Education*, *13*(3), 580–594. DOI: 10.3390/ejihpe13030045 PMID: 36975397

Koc, S., & Liu, X. (2016). An investigation of graduate students' help-seeking experiences, preferences and attitudes in online learning. *The Turkish Online Journal of Educational Technology*, *15*, 27–38. https://api.semanticscholar.org/CorpusID:151851517

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, *11*(4), 1–10. DOI: 10.4018/ijec.2015100101

Korlat, S., Kollmayer, M., Holzer, J., Lüftenegger, M., Pelikan, E. R., Schober, B., & Spiel, C. (2021). Gender differences in digital learning during COVID-19: Competence beliefs, intrinsic value, learning engagement, and perceived teacher support. *Frontiers in Psychology*, *12*, 637776. DOI: 10.3389/fpsyg.2021.637776 PMID: 33868109

Kumar, P. S. (2024). Technostress: A comprehensive literature review on dimensions, impacts, and management strategies. *Computers in Human Behavior Reports*, *16*, 2451–9588. DOI: 10.1016/j.chbr.2024.100475

Lanzl, J. (2023). Social support as technostress inhibitor. *Business & Information Systems Engineering*, *65*(3), 329–343. DOI: 10.1007/s12599-023-00799-7

Lazarus, R., & Folkman, S. (1984). *Stress. Appraisal and coping*. Springer.

Lu, H. P., & Chiou, M. J. (2010). The impact of individual differences on e-learning system satisfaction: A contingency approach. *British Journal of Educational Technology*, *41*(2), 307–323. DOI: 10.1111/j.1467-8535.2009.00937.x

Ma, Y., & Turel, O. (2019). Information technology use for work and technostress: Effects of power distance and masculinity culture dimensions. *Cognition Technology and Work*, *21*(1), 145–157. DOI: 10.1007/s10111-018-0503-1

Machado-Da-Silva, F. N., Meirelles, F. S., Filenga, D., & Brugnolo Filho, M. (2014). Student satisfaction process in virtual learning system: Considerations based in information and service quality from Brazil's experience. *Turkish Online Journal of Distance Education*, *15*(3), 122–142. DOI: 10.17718/tojde.52605

Marikyan, D., & Papagiannidis, S. (2025). Technology acceptance model: A review. In Papagiannidis, S. (Ed.), *Theory hub book* (pp. 244–262). https://open.ncl.ac.uk

Mohammed, L. A., Aljaberi, M. A., Amidi, A., Abdulsalam, R., Lin, C. Y., Hamat, R. A., & Abdallah, A. M. (2022). Exploring factors affecting graduate students' satisfaction toward e-learning in the era of the COVID-19 crisis. *European Journal of Investigation in Health, Psychology and Education*, *12*(8), 1121–1142. DOI: 10.3390/ejihpe12080079 PMID: 36005228

Nastjuk, I., Trang, S., Grummeck-Braamt, J. V., Adam, M. T. P., & Tarafdar, M. (2024). Integrating and synthesising technostress research: A meta-analysis on technostress creators. Outcomes. and IS usage contexts. *European Journal of Information Systems*, *33*(3), 361–382. DOI: 10.1080/0960085X.2022.2154712

Organization for Economic Cooperation and Development (OECD). (2023). *OECD digital education outlook 2023: Towards an effective digital education ecosystem*. OECD Publishing. DOI: 10.1787/c74f03de-

Perugini, M., Gallucci, M., & Costantini, G. (2018). A practical primer to power analysis for simple experimental designs. *Revue Internationale de Psychologie Sociale*, *31*(1), 1–23. DOI: 10.5334/irsp.181

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, *63*(1), 539–569. DOI: 10.1146/annurev-psych-120710-100452 PMID: 21838546

Prensky, M. (2001). Digital natives, digital immigrants, part 1. *On the Horizon*, *9*(5), 3–6. DOI: 10.1108/10748120110424816

Qazi, A., Hasan, N., Abayomi-Alli, O., Hardaker, G., Scherer, R., Sarker, Y., Paul, S. K., & Maitama, J. Z. (2022). Gender differences in information and communication technology use & skills: A systematic review and meta-analysis. *Education and Information Technologies*, *27*(3), 4225–4258. DOI: 10.1007/s10639-021-10775-x PMID: 34697533

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Qiang, T. (2008). The consequences of technostress for end users in organization: Conceptual development and empirical validation. *Information Systems Research*, *19*(4), 417–433. DOI: 10.1287/isre.1070.0165

Roman, M., & Plopeanu, A. P. (2021). The effectiveness of the emergency e-learning during COVID-19 pandemic. The case of higher education in economics in Romania. *International Review of Economics Education*, *37*, 100218. Advance online publication. DOI: 10.1016/j.iree.2021.100218

Saleem, F., Chikhaoui, E., & Malik, M. I. (2024). Technostress in students and quality of online learning: Role of instructor and university support. *Frontiers in Education*, *9*, 1309642. DOI: 10.3389/feduc.2024.1309642

Schaufeli, W. B., & Taris, T. W. (2014). A critical review of the job demands-resources model: Implications for improving work and health. In G. F. Bauer & O. Hämmig (Eds.), *Bridging occupational, organizational and public health: A transdisciplinary approach* (pp. 43–68). Springer Science+Business Media Dordrecht. DOI: 10.1007/978-94-007-5640-3_4

Selwyn, N. (2023). Lessons to be learnt? Education, techno-solutionism, and sustainable development. In Sætra, H. S. (Ed.), *Technology and sustainable development* (pp. 71–83). Routledge. DOI: 10.1201/9781003325086-6

Shams, M. S., Niazi, M. M., Gul, H., Mei, T. S., & Khan, K. U. (2022). e-Learning adoption in higher education institutions during the COVID-19 pandemic: A multigroup analysis. *Frontiers in Education*, *6*, 783087. DOI: 10.3389/feduc.2021.783087

Simon, P., Jiang, J., & Fryer, L. K. (2023). Measurement of higher education students' and teachers' experiences in learning management systems: A scoping review. *Assessment & Evaluation in Higher Education*, *49*(4), 441–452. DOI: 10.1080/02602938.2023.2266154

Šorgo, A., Crnkovič, N., Gabrovec, B., Cesar, K., & Selak, Š. (2022). Influence of forced online distance education during the COVID-19 pandemic on the perceived stress of postsecondary students: Cross-sectional study. *Journal of Medical Internet Research*, *24*(3), e30778. DOI: 10.2196/30778 PMID: 35171098

Sverdlyka, Z., Klynina, T., Fedushko, S., & Bratus, I. (2022). YouTube Web-Projects: Path from entertainment Web content to online educational tools. In Kryvinska, N., & Greguš, M. (Eds.), *Developments in information & knowledge management for business applications. Studies in systems, decision and control* (*Vol. 421*, pp. 491–512). Springer. DOI: 10.1007/978-3-030-97008-6_22

Tarafdar, M., Cooper, C. L., & Stich, J. F. (2019). The technostress trifecta: Techno eustress, techno distress and design: Theoretical directions and an agenda for research. *Information Systems Journal*, *29*(1), 6–42. DOI: 10.1111/isj.12169

Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., & Ragu-Nathan, T. S. (2007). The impact of technostress on role stress and productivity. *Journal of Management Information Systems*, *24*(1), 301–328. DOI: 10.2753/MIS0742-1222240109

Tarafdar, M., Tu, Q., Ragu-Nathan, T. S., & Ragu-Nathan, B. S. (2011). Crossing to the dark side: Examining creators, outcomes, and inhibitors of technostress. *Communications of the ACM*, *54*(9), 113–120. DOI: 10.1145/1995376.1995403

Turel, O., & Gaudioso, F. (2018). Techno-stressors, distress and strain: The roles of leadership and competitive climates. *Cognition Technology and Work*, *20*(2), 309–324. DOI: 10.1007/s10111-018-0461-7

United Nations Educational, Scientific and Cultural Organization. (2020). *COVID-19 response – Remote learning strategy as a key element in ensuring continued learning*. https://en.unesco.org/covid19/educationresponse/

Upadhyaya, P., & Vrinda, . (2021). Impact of technostress on academic productivity of university students. *Education and Information Technologies*, *26*(2), 1647–1664. DOI: 10.1007/s10639-020-10319-9

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *Management Information Systems Quarterly*, *27*(3), 425–478. DOI: 10.2307/30036540

Verbree, A. R., Hornstra, L., Maas, L., & Wijngaards-de Meij, L. (2023). Conscientiousness as a predictor of the gender gap in academic achievement. *Research in Higher Education*, *64*(3), 451–472. DOI: 10.1007/s11162-022-09716-5 PMID: 35991353

Wang, C., Xie, A., Wang, W., & Wu, H. (2020). Association between medical students' prior experiences and perceptions of formal online education developed in response to COVID-19: A cross-sectional study in China. *BMJ Open*, *10*(10), e041886. DOI: 10.1136/bmjopen-2020-041886 PMID: 33122327

Wang, X., Li, Z., Ouyang, Z., & Xu, Y. (2021). The Achilles heel of technology: How does technostress affect university students' wellbeing and technology-enhanced learning. *International Journal of Environmental Research and Public Health*, *18*(23), 12322. DOI: 10.3390/ijerph182312322 PMID: 34886048

Weerasinghe, I. M. S., & Fernando, R. L. S. (2018). University facilities and student satisfaction in Sri Lanka. *International Journal of Educational Management*, *32*(5), 866–880. DOI: 10.1108/IJEM-07-2017-0174

Zhai, X. Y., Lei, D. C., Zhao, Y., Jing, P., Zhang, K., Han, J. T., Ni, A. H., & Wang, X. Y. (2023). Surviving the shift: College student satisfaction with emergency online learning during COVID-19 pandemic. *World Journal of Psychiatry*, *13*(12), 1106–1120. DOI: 10.5498/wjp.v13.i12.1106 PMID: 38186724

Zhang, Z., Cao, T., Shu, J., & Liu, H. (2020). Identifying key factors affecting college students' adoption of the e-learning system in mandatory blended learning environments. *Interactive Learning Environments*, *30*(8), 1388–1401. DOI: 10.1080/10494820.2020.1723113

APPENDIX A

Composite Reliability for Each Reflective Investigated Construct and HTMT

Variables	Composite reliability			HTMT							
	Cronbach's alpha	Composite reliability	Average Variance Extracted (AVE)	Satisfaction (HTMT)	1	2	3	4	5	6	7
1. TI involvement facilitation	.74	.84	.57	.36	-						
2. TI literacy facilitation	.81	.86	.55	.43	.80						
3. TI techno support	.90	.93	.77	.30	.56	.74					
4. TS complexity	.89	.92	.69	.45	.22	.32	.29				
5. TS insecurity	.80	.86	.56	.47	.27	.35	.31	.87			
6. TS uncertainty	.83	.89	.66	.16	.19	.21	.12	.52	.53		
7. TS invasion	.89	.92	.75	.37	.34	.39	.33	.59	.67	.33	
8. TS overload	.90	.92	.71	.41	.31	.38	.33	.63	.72	.38	.89

Note. TI = Technoinhibitors; TS=Technostressors

APPENDIX B

Descriptive Statistics for DV Explored

DV	IV				IV			
	Year of research	Gender	Mean	SD	Year of research	Field of study	Mean	SD
Satisfaction	2020	Women	7.30	2.31	2020	SSHA	7.19	2.41
		Men	6.32	2.66		STEM	6.65	2.53
		Total	6.98	2.47		Total	6.98	2.47
	2023	Women	7.63	2.25	2023	SSHA	7.72	2.19
		Men	7.40	2.27		STEM	7.36	2.30
		Total	7.53	2.26		Total	7.53	2.26
Use of LMS	2020	Women	32.68	6.14	2020	SSHA	32.53	6.51
		Men	30.44	5.94		STEM	30.99	5.69
		Total	31.95	6.09		Total	31.94	6.25
	2023	Women	32.14	6.23	2023	SSHA	32.39	5.73
		Men	31.49	6.1		STEM	31.38	6.23
		Total	31.86	6.16		Total	31.87	6.00
Overall technostress creators	2020	Women	14.81	3.65	2020	SSHA	14.70	3.72
		Men	14.06	3.63		STEM	14.33	35.5
		Total	14.56	3.66		Total	14.56	3.66
	2023	Women	12.07	3.41	2023	SSHA	11.92	3.39
		Men	11.50	3.67		STEM	11.76	3.66
		Total	11.8	3.53		Total	11.84	3.53
Techno-overload	2020	Women	3.42	.94	2020	SSHA	3.38	.97
		Men	3.26	.99		STEM	3.34	.96
		Total	3.37	.96		Total	3.37	.96
	2023	Women	2.62	.99	2023	SSHA	2.57	.94
		Men	2.50	.99		STEM	2.57	1.03
		Total	2.57	.99		Total	2.57	.99
Techno-invasion	2020	Women	3.43	1.07	2020	SSHA	3.39	1.10
		Men	3.19	1.05		STEM	3.30	1.02
		Total	3.35	1.07		Total	3.35	1.07
	2023	Women	2.64	1.12	2023	SSHA	2.55	1.09
		Men	2.39	1.07		STEM	2.52	1.12
		Total	2.53	1.10		Total	2.53	11.1
Techno-complexity	2020	Women	2.49	.95	2020	SSHA	2.50	.98
		Men	2.38	.97		STEM	2.38	.92
		Total	2.46	.95		Total	2.46	.96
	2023	Women	2.09	.80	2023	SSHA	2.08	.81
		Men	2.01	.82		STEM	2.03	.82
		Total	2.05	.81		Total	2.05	.81

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DV	IV		Mean	SD	IV		Mean	SD
	Year of research	Gender			Year of research	Field of study		
Techno-insecurity	2020	Women	2.71	.91	2020	SSHA	2.69	.93
		Men	2.63	.89		STEM	2.67	.88
		Total	2.68	.91		Total	2.68	.91
	2023	Women	2.23	.81	2023	SSHA	2.23	.81
		Men	2.20	.86		STEM	2.20	.85
		Total	2.21	.83		Total	2.21	.83
Techno-uncertainty	2020	Women	2.76	.74	2020	SSHA	2.75	.74
		Men	2.59	.78		STEM	2.63	.78
		Total	2.70	.76		Total	2.70	.76
	2023	Women	2.51	.78	2023	SSHA	2.49	.77
		Men	2.41	.77		STEM	2.44	.79
		Total	2.47	.78		Total	2.47	.78
Overall Techno-inhibitors	2020	Women	9.07	1.95	2020	SSHA	9.06	1.93
		Men	8.66	1.93		STEM	8.73	1.98
		Total	8.93	1.95		Total	8.93	1.95
	2023	Women	9.41	1.95	2023	SSHA	9.58	1.94
		Men	9.15	2.18		STEM	9.06	2.12
		Total	9.30	2.05		Total	9.30	2.05
Literacy facilitation	2020	Women	3.04	.83	2020	SSHA	3.03	.827
		Men	2.82	.84		STEM	2.87	.839
		Total	2.97	.83		Total	2.97	.83
	2023	Women	3.21	.80	2023	SSHA	3.26	.81
		Men	3.07	.85		STEM	3.05	.83
		Total	3.15	.82		Total	3.151	.83
Technical support	2020	Women	3.30	.72	2020	SSHA	3.29	.69
		Men	3.20	.70		STEM	3.24	.76
		Total	3.27	.71		Total	3.27	.72
	2023	Women	3.43	.78	2023	SSHA	3.47	.78
		Men	3.32	.83		STEM	3.31	.81
		Total	3.38	.80		Total	3.39	.80
Involvement facilitation	2020	Women	2.72	.75	2020	SSHA	2.73	.78
		Men	2.63	.81		STEM	2.61	.77
		Total	2.69	.77		Total	2.69	.78
	2023	Women	2.77	.74	2023	SSHA	2.84	.77
		Men	2.76	.86		STEM	2.69	.81
		Total	2.77	.80		Total	2.77	.80

Note. 2020: W (Women) = 419, M (Men) = 203; 2023: W = 495, M = 353. 2020: SSHA (Social Sciences Humanities and Arts) = 387, STEM (Science, Technology, Engineering and Mathematics) = 235; 2023: W = 403, M = 445.

APPENDIX C

Tests of Between-Subjects Effects

Dependent variable	Independent variables	Research year * Gender			Independent variables	Research year * Field of study		
		F/W*	Sig.	Partial η^2		F	Sig.	Partial η^2
Satisfaction $R^2 = .03/.02$	Research year	29.79	< .001	.020	Research year	24.58	< .001	.016
	Gender	22.13	< .001	.015	Field of study	12.84	< .001	< .01
	Research year * Gender	8.77	.003	< .01	Research year * Field of study	0.52	.47	< .01
LMS use $R^2 = .01/.01$	Research year	0.58	.45	< .01	Research year	0.17	.68	< .01
	Gender	18.51	< .001	.012	Field of study	15.24	< .001	.01
	Research year * Gender	5.65	.02	< .01	Research year * Field of study	0.64	.42	< .01
Overall technostress creators $R^2 = .13/.13$	Research year	179.90	< .001	.109	Research year	192.73	< .001	.116
	Gender	11.14	.001	< .01	Field of study	1.96	.16	< .01
	Research year * Gender	0.21	.65	< .01	Research year * Field of study	0.28	.60	< .01
Techno-overload $R^2 = .14/.14$	Research year	209.71	< .001	.125	Research year	227.89	< .001	.135
	Gender	6.67	.010	< .01	Field of study	0.10	.75	< .01
	Research year * Gender	0.19	.66	< .01	Research year * Field of study	0.08	.78	< .01
Techno-invasion $R^2 = .13/.12$	Research year	179.57	< .001	.109	Research year	190.76	< .001	.115
	Gender	16.84	< .001	.011	Field of study	1.11	.29	< .01
	Research year * Gender	0.01	.91	< .01	Research year * Field of study	0.21	.64	< .01
Techno-complexity $R^2 = .05/.05$	Research year *Welch test*	65.64	< .001	.043	Research year *Welch test*	67.49	<.001	< .01
		72.18	*< .001*			*72.18*	*<.001*	
	Gender *Welch test*	3.47	.06	< .01	Field of study *Welch test*	3.39	.07	< .01
		6.62	*.001*			*6.62*	*.01*	
	Research year * Gender	0.08	.78	< .01	Research year * Field of study	0.51	.48	< .01

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Dependent variable	**Independent variables**	**Research year * Gender**			**Independent variables**	**Research year * Field of study**		
		F/W*	**Sig.**	**Partial η^2**		**F**	**Sig.**	**Partial η^2**
Techno-insecurity $R^2 = .07/.07$	Research year *Welch test*	92.08	< .001	< .01	Research year	100.50	< .001	.064
		102.74	*< .001*		*Welch test*	102.74	< .001	
	Gender *Welch test*	1.16	.28	< .01	Field of study *Welch test*	0.21	.65	< .01
		3.4	*.06*			*3.65*	*.06*	
	Research year * Gender	0.31	.58	< .01	Research year * Field of study	0.01	.93	< .01
Techno-uncertainty $R^2 = .03/.03$	Research year	25.82	< .001	< .01	Research year	28.41	< .001	.019
	Gender	9.81	.002	< .01	Field of study	4.08	.04	< .01
	Research year * Gender	0.65	.42	< .01	Research year * Field of study	0.57	.45	< .01
Overall techno-inhibitors $R^2 = .01/.02$	Research year	14.56	< .001	.010	Research year	15.64	< .001	.01
	Gender	9.11	.003	< .01	Field of study	15.64	< .001	.01
	Research year * Gender	0.48	.49	< .01	Research year * Field of study	0.83	.36	< .01
Literacy facilitation $R^2 = .02/.02$	Research year	20.41	< .001	.01	Research year	21.19	< .001	.014
	Gender	15.24	< .001	.01	Field of study	17.59	< .001	.012
	Research year * Gender	0.81	.37	< .01	Research year * Field of study	.30	.58	< .01
Technical support $R^2 = .01/.01$	Research year *Welch test*	8.54	.004	< .01	Research year *Welch test*	9.19	.002	< .01
		3.55	*.06*			*8.35*	*.004*	
	Gender *Welch test*	5.99	.02	< .01	Field of study *Welch test*	6.66	.01	< .01
		4.9	*.03*			*5.91*	*.02*	
	Research year * Gender	0.006	.94	< .01	Research year * Field of study	2.19	.14	< .01
Involvement facilitation $R^2 = .004/.01$	Research year *Welch test*	4.56	.03	< .01	Research year *Welch test*	5.20	.02	< .01
		3.52	*.06*			*3.55*	*.06*	
	Gender *Welch test*	1.47	.23	< .01	Field of study *Welch test*	9.92	.002	< .01
		.72	*.40*			*8.64*	*.003*	
	Research year * Gender	0.80	.37	< .01	Research year * Field of study	.09	.76	< .01

Note. R^2 - R squared for the first pair of IV/ for the second pair of IV; η^2- Partial Eta Square; the values of partial η^2 lower than .005 were replaced with < .01. * F test and Welch test.

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