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# Teaching after the pandemic: The role of technostress and organizational support on intentions to adopt remote teaching technologies

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A R T I C L E  I N F O

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A B S T R A C T

The ongoing COVID-19 pandemic has led to several changes in academic teaching practices. Although educational digital technologies have been crucial during the initial phases of the pandemic, their forced adoption has led to negative consequences.

In the present study, we aimed to integrate the Technology Acceptance Model theoretical framework (Davis, 1989) by exploring the effects of some possible factors that influence the willingness to adopt digital learning tools in the future when the pandemic is over. Among them, technostress was considered one of the external factors that could have adversely affected digital teaching technology adoption in the future. In contrast, the perception of technical support offered by the university was considered a potential protective factor.

A total of 463 Italian university faculty completed an online questionnaire at the end of the first semester (a.y. 2020–21). The frequency of distance teaching technologies usage behavior was measured objectively by extracting teachers' activities from the University's e-learning databases. Key findings indicated that distance teaching technologies' frequency of use increased technostress, which in turn negatively impacted the perception of ease of use. The latter influences - both directly and indirectly through perceived usefulness - the intentions to adopt distance learning tools after the pandemic. Organizational support negatively predicted technostress. Implications to help public institutions develop functional strategies to cope with the technological changes brought by the pandemic are discussed.

The Covid-19 pandemic drastically altered public and private balances, considering its profound impact on human life and global economies (Xiang et al., 2020). Many governments implemented a strict lockdown to limit the spread of the virus and reduce fatalities from the disease. In Italy, for example, citizens were confined at home from March to May 2020, and all non-essential productive activities were stopped. Moreover, the Covid outbreak also prompted the closure of schools and universities, becoming a critical challenge for the entire educational sector (Peimani & Kamalipour, 2021).

In this regard, universities tried to reorganize themselves very quickly. First, they implemented a series of prevention measures for the health and safety of the academic community; then, they reshaped their activities to deal effectively with the emergency. Mainly, academics tried to devise an alternative to the face-to-face technique (Dwidienawati et al., 2020) not to suspend teaching programs, although some activities related to learning, teaching, and assessment were inevitably stopped or readjusted (Peimani & Kamalipour, 2021). Therefore, in the first months of the emergency, they engaged in a typical emergency remote teaching, which is a temporary transition from instructional delivery to an alternative delivery mode due to crisis circumstances (Hodges et al., 2020). In the following months, they adopted several forms of remote teaching: blended, hybrid, and distance learning (Ní Fhloinn & Fitzmaurice, 2021). In addition, exams, conferences, seminars, and other academic events were modified, postponed, or canceled (Mohd Satar et al., 2020).

The education system transformed through digital media into a formative online offer (Di Palma & Belfiore, 2020). Technology has significantly influenced didactical techniques (Chou & Chou, 2021; Peimani & Kamalipour, 2021). Notably, the imposition of the “remote” modality and the lack of a transition and training phase contributed to the emergence of stress (Li & Wang, 2021). This aspect was particularly salient, considering that new technologies are generally successful only if employees accept and desire them (Davis, 1989; Venkatesh et al., 2003). Understanding whether employees will embrace new

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technologies before implementing them in the workplace is essential. The well-establish Technology Acceptance Model (TAM; Davis, 1989) allows us to investigate how employees intend to utilize these technologies and how useful/easily they are regarded to be. This model has undergone updates demonstrating the potential for additional external factors that can influence the acceptance of technology and, in turn, its use (Marangunić & Granić, 2015; Taherdoost, 2019).

Therefore, based on this evidence, the present work aimed to test the role of technostress and perceived technical support as possible external factors that could directly or indirectly influence the intention to use digital technologies for remote teaching even after the COVID-19 pandemic.

## 1. Online teaching during the Covid-19 pandemic and technostress

The use of digital technologies has become a necessary and widespread solution, although, before the Covid-19 emergency, it was not widely adopted in Italy. Italy's current policy framework for digital education is the Italian *National Plan for Digital Education* (NPDE), launched by the Ministry of Education, University, and Research to set up a comprehensive innovation strategy across Italy's educational system and bring it into the digital age. Unfortunately, no data regarding the effect of the activities implemented in this plan has been made public so far. Nevertheless, one national survey (Epasto, 2015) showed that 41,5 % of Italian university teachers reported only superficial knowledge of Information and Communication Technology (ICT) and a lack of interest in integrating ICT into teaching (Epasto, 2015).

Moreover, although ICT brought numerous benefits to education and higher education, such as the possibility to discover helpful teaching strategies and resources, as well as the flexibility offered by online instruction (Chou & Chou, 2021; Li & Wang, 2021), new technologies increased the risk of information overload as well as the workload of both professors and students (Raja & Nagasubramani, 2018). Indeed, changes in learning and teaching practices caused by using ICT place greater demands on university teachers (e.g., time pressure and the need for constant upgrade of knowledge and skills), who must devote more time and effort to adapting to these changes (Jena, 2015; Syvänen et al., 2016). This means that high levels of digital technology use may increase effort and working rate, as well as multitasking and interruptions, resulting in long-term stress (Chesley, 2014).

Mainly, technostress has been defined as "the stress that users experience as a result of application multitasking, constant connectivity, information overload, frequent system upgrades, and consequent uncertainty, continual relearning and consequent job-related insecurities, and technical problems associated with the organizational use of ICT" (Tarafdar et al., 2010, pp. 304–305). Technostress, therefore, is not a direct consequence of the technology, but it arises from the interaction between users and digital technologies (Signore et al., 2021).

Technostress research has primarily concentrated on the industrial and government sectors, with less attention paid to education (Li & Wang, 2021; Panisoara et al., 2020). Evidence from the literature showed several symptoms of technostress, such as anxiety, physical diseases, mental fatigue, technophobia, irritability, exhaustion, and insomnia (Arnetz & Wiholm, 1997). Recent research has discovered poorer worker productivity, job performance, job satisfaction, and organizational commitment, as well as lower ICTs use intentions and more excellent turnover intentions, as some of the most common effects of technostress (La Torre et al., 2019).

One recent study (Molino et al., 2020) in the Italian context proposed several stress creators deriving from the use of technologies, namely the perception of overload due to technologies (work-overload), the risk of intrusion of work and technology into the personal life (techno-invasion), and the feeling of inadequacy due to the perception of ICTs' complexity (techno-complexity). Grounded in the literature, we expected that the use of digital technologies would result in an increased perception of technostress; that is, the increase in the use of digital technology during the pandemic would have had a positive relationship with technostress creators (HP1).

## 2. The technology acceptance model and external variables: the role of technostress and organizational support

As stated, the Covid-19 outbreak obliged academics and students to adapt quickly to new teaching and learning strategies mediated by new technologies. Although the use of technology in education is encouraged, some studies have identified several barriers to overcome, including a lack of training, insufficient infrastructure, and a lack of support from technology specialists, among others (Panisoara et al., 2020).

Moreover, it is well-known that for the effective implementation of technologies in the organization, it is crucial to understand the technology acceptance by users (Davis, 1989; Venkatesh et al., 2003). One of the most applied theoretical models to explain technology acceptance in several contexts is the Technology Acceptance Model (TAM; Davis, 1989; Paganin et al., 2022; Sagnier et al., 2020).

The TAM has been developed based on the Theory of Reasoned Action (TRA) (Fishbein, 1967; Fishbein & Ajzen, 1975). The TAM takes into consideration three principal dimensions: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioral Intention to Use (INT). PU is the extent to which a person estimates that a given technology can help him/her achieve his/her work-related goals. On the other hand, PEOU is the degree to which a person believes such technology is easy to use to perform the intended tasks. Further, INT is defined as the likelihood that a person will use that technology. PU and PEOU are the primary users' perceptions leading to acceptance (Venkatesh & Davis, 2000).

Subsequent revisions of this model have shown that other external variables could help in understanding the acceptance of technology and, in turn, its use (Marangunić & Granić, 2015; Taherdoost, 2019). A common aspect of these revisions relies on the consideration that other variables, besides PU and PEOU, may influence the acceptance and intention to use a given technology (Svendsen et al., 2013), even if PU seems to be one of the most relevant predictors of INT (Davis, 1989).

To the best of our knowledge, it has yet to be extensively explored to what extent technostress influences the intention to use technologies. A study by Kim and Park (2018) found that technostress creates innovation-resistance, which leads to a lower intention to use, while the direct relationship between technostress and intention to use was not significant. Moreover, Joo and Shin (2020) found that technostress was negatively associated with secondary education teachers' intention to use technology for teaching. A recent study conducted in Taiwan showed that technostress was related to teachers' discontinuance of their intention to use online teaching among primary and secondary school teachers but not among university professors (Chou & Chou, 2021).

However, the previously cited research did not measure the effects of technostress on core TAM dimensions (namely PU and PEOU). In the present work, we posited that examining technostress experienced by university teachers is critical to understanding technology acceptance in higher education. Therefore, we aimed to incorporate technostress into the TAM as a relevant external factor affecting the technology adoption process (Wang et al., 2008; see Fig. 1 for the hypothesized theoretical model).

More in detail, we expected that teachers' technostress resulting from mandated online teaching in the pandemic would have been negatively associated with the intention to use online teaching, both directly and indirectly, through PEOU.

Nevertheless, unlike the classic TAM postulates (i.e., PU and PEOU predict INT), we did not hypothesize a mediating effect of PU on the relationship between technostress and intentions. In fact, at the time the present study was conducted (during the ongoing Covid-19 pandemic), the use of technology for remote teaching was the only option.

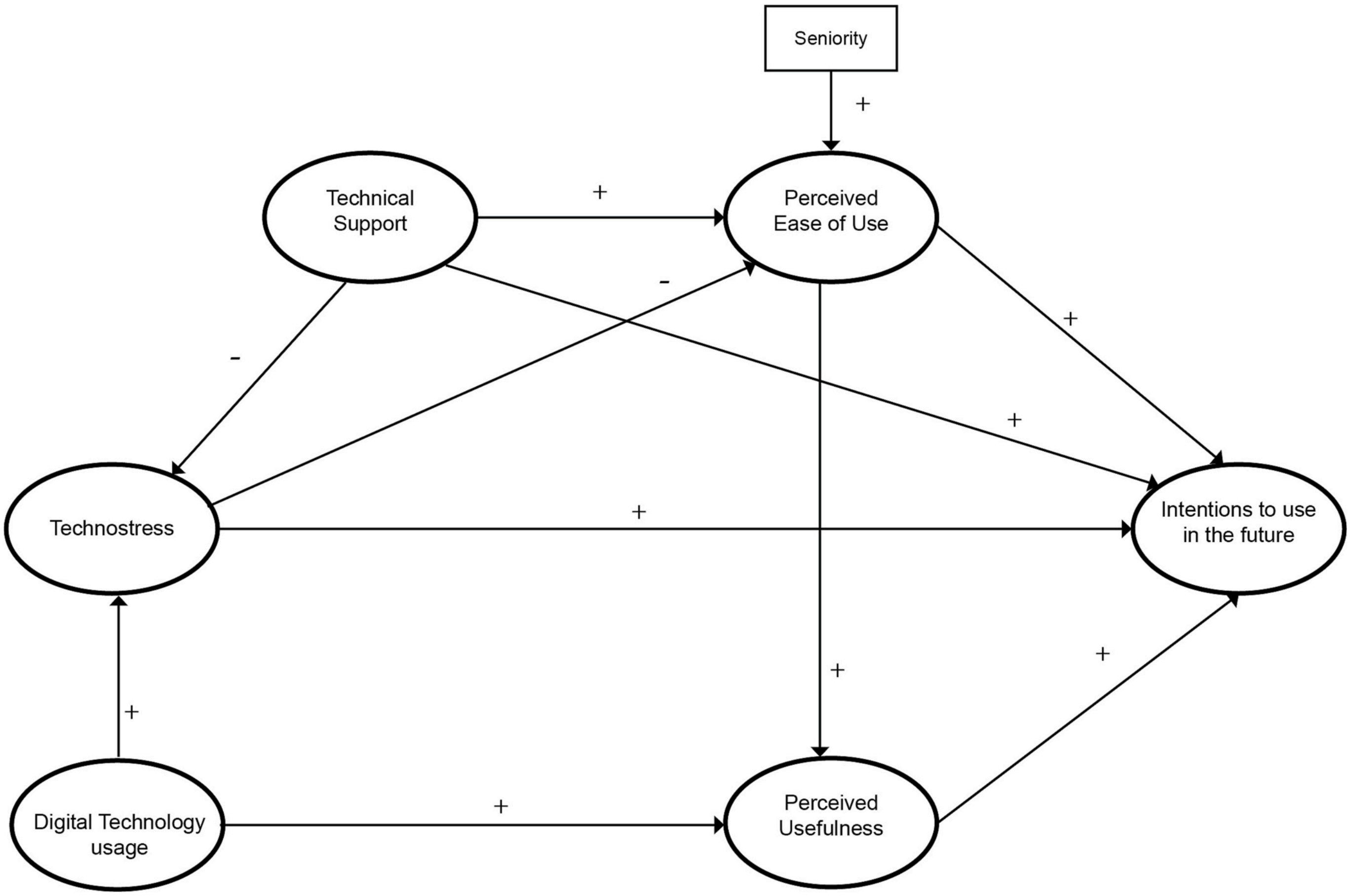


**Fig. 1.** Theoretical hypothesized model.

Therefore, we hypothesized technostress to be directly and negatively associated with PEOU (HP2a) and with the intention to use online teaching after the pandemic in the future (HP2b). We also speculated that PEOU would have mediated the relationship between technostress and intention to use online teaching technologies in the future (HP2c). Similarly, we hypothesized that the frequency of use of such technologies may have influenced PU (HP2d). In other words, the greater the use of such technologies, the more teachers perceive their usefulness in being able to continue with teaching activities. Moreover, since the TAM states that the perception of ease of use influences usefulness (Venkatesh & Davis, 2000), we also hypothesized a serial mediation: PEOU and PU serially mediate the relationship between technostress and intention to use online teaching (HP2e). In contrast, PU mediates the relationship between the use of digital technology during the pandemic and intentions (HP2f).

Among the external variables that could help understand the acceptance of new technology, organizational support is a critical factor in facilitating such adoption (Park et al., 2018). Indeed, some studies found significant relationships between organizational support and the intention to use (Tanduklangi, 2017), as well as the usefulness/ease of use of technology (Bhattacherjee & Hikmet, 2008; Tuan & Venkatesh, 2010). On the contrary, a lack of organizational support can undermine the company's efforts to introduce new technology (Naujokaitiene et al., 2015; Park et al., 2018). Notably, in the present study, we focused on technical support, which refers to the availability of professional individuals (e.g., help desk, information center) to answer user inquiries about technology use and provide theoretical and/or hands-on support to users before and during use (Bhattacherjee & Hikmet, 2008). As shown by previous studies, technical support is targeted at improving actual utilization rather than user perceptions of utility: indeed, Bhattacherjee and Hikmet (2008) demonstrated that technical support motivated intention by influencing organizational members' perceived ease of use of technology usage; therefore, we do not expect this construct to influence perceived utility, but only the intention to use, as well as the perception of ease-of-use online teaching. These considerations lead to the hypothesis that technical support would have been positively associated with the intention to use (HP3a) and PEOU (HP3b). In line with the previous predictions, we also hypothesized a mediational effect of PEOU in the relationship between the perception of technical support and INT (HP3c).

Finally, several studies claimed that organizational support (i.e., technical support) represents one of the most critical organizational mechanisms that can potentially reduce the effects of technostress (Ragu-Nathan et al., 2008). Notably, it has been recognized as one of the technostress inhibitors presented by Li and Wang (2021) to combat the impacts of technostress. Indeed, it has been established that the organization's support has a substantial impact on reducing employees' computer anxiety, which in turn affects stress associated with computer use (Kim et al., 2016). This means that it is crucial for organizations to activate support systems to reduce technostress (Bondanini et al., 2020; Norhisham, 2021). Thus, we hypothesized that the technical support offered by the organization would have been negatively associated with technostress (HP3d). Moreover, we also hypothesized that PEOU and PU would have serially mediated the relationship between perceived technical support and intention to use online teaching in the future (HP3e).

## 3. Method

### 3.1. Participants and procedure

The current data is part of a larger dataset collected between March 8th and April 15th, 2021, and part of the research project titled “Giving value to the pandemic emergency. Indicators of quality to evaluate teaching practice and design curricular and community-oriented training proposals”, funded by the University Milano Bicocca (Project end: December 2022). The project aimed to gather data regarding the use of digital technologies adopted during the pandemic to provide educational activities.

After obtaining consent from the University Data Protection Office of the University of Milano-Bicocca, an invitation to participate in the data collection was emailed to all faculty with an initial message on March 8th. To encourage the participation of as many faculties as possible, a second message was sent on March 13th, a third message on March 18th, and a fourth email was delivered on March 24th, 2021.

The internal IT office provided the mailing list, whose managers extracted the contact information for all faculty who had taught at least one course during the first semester of the 2020–2021 academic year ($N = 1482$) from the university databases.

A total of 722 faculty accessed the survey, implemented through the Qualtrics web survey system. The system was set up so that each faculty member could only respond once to the questionnaire. Nevertheless, some faculty reported answering the questionnaire more than once. Thus, data were first inspected for duplicate cases ($N = 66$). Only responses given on the first login were considered for each duplicated case. Therefore, the number of unique cases was $N = 656$. Of these, 47 individuals did not consent to process their data and were therefore not considered in the final sample. Of the remaining 609 participants, 146 presented missing data (i.e., >25 % missing data). Standard criteria for exclusion in case of missing data suggests that data analysis is likely to be biased when >10 % of data are missing (Bennett, 2001; Lodder, 2013); therefore, these participants were not considered. Thus, the final sample consisted of 463 participants (response rate = 31.2 %; 50.5 % female, $M_{age} = 47.98$, $SD = 10.64$) and was composed of post-doc fellows (5.8 %), assistant professors (16.3 %), associate professors (33 %), full professors (18.5 %), and guest lecturers (26.4 %).

### 3.2. Measures

#### 3.2.1. Technostress creators

To measure the technostress creators, we adopted the Italian Translation of the Technostress Creators Scale (Molino et al., 2020) consisting of 11 items taken from the technostress creators scale (Ragu-Nathan et al., 2008; Tarafdar et al., 2019). The scale tapped three different constructs: techno-overload (4 items; sample item: “During the previous semester, I was forced by technology for remote teaching to do more work than I can handle”), techno-invasion (3 items; sample item: “During the previous semester I spend less time with my family due to technology for remote teaching”) and techno-complexity (4 items, sample item: “I need a long time to understand and use new technologies for remote teaching”). Participants used a Likert scale from 1 = *strongly disagree* to 5 = *strongly agree*.

#### 3.2.2. Perceived Ease Of Use (PEOU)

PEOU (3 items; sample item: “Learning how to use technology for online teaching was easy for me”) was measured using the scale proposed by Davis (1989). The scale was both anchored on a 5-point Likert scale ranging from 1 = *strongly disagree* to 5 = *strongly agree*.

#### 3.2.3. Perceived Usefulness (PU)

PU (3 items; sample item: “I find technologies for online teaching useful”) was measured using the scale proposed by Davis (1989) anchored on a 5-point Likert scale ranging from 1 = *strongly disagree* to 5 = *strongly agree*.

#### 3.2.4. Intentions to adopt digital technologies for teaching after the pandemic (INT)

INT was measured by adopting the Italian version (Curcuruto et al., 2009) of Venkatesh and Davis' s (2000) Intention to Use scale (3 items; sample item: “I anticipate that, should they be available to me in the future, I will use online teaching technologies in my teachings”) a 5-point Likert scale ranging from 1 = *strongly disagree* to 5 = *strongly agree*.

#### 3.2.5. Technical support

To measure the level of technical support offered by the university, an ad hoc scale consisting of 3 items was created: “When I encountered difficulties using technology for online teaching, a specific person was available to provide me with assistance”, “When I encountered difficulties using online teaching technologies, I knew where to seek assistance” and “When I encountered difficulties using online teaching technology a specific person was available to provide me assistance” (1 = *strongly disagree* to 5 = *strongly agree).*

#### 3.2.6. Actual use of online educational technologies

Two different indicators were combined to measure the use of online technologies during the semester of teaching during the pandemic. A first self-reported item was adopted, asking participants to report the actual teaching hours carried out between October 2020 and February 2021. This index was combined with data extracted from the database of the e-learning platform provided by the University of Milano Bicocca (Moodle). An extraction of the usage data was performed for each participant, creating a composite index given by the sum of the frequency of use of the following features offered by Moodle during the period between October 1st, 2020, and February 1st, 2021: count of updates/news posted, count of assignments created, count of files uploaded, and count of sections/topics created. A single count was extracted for each feature made available by the e-learning system. The sum of all the activities carried out during the first semester represented the frequency of use of distance teaching technologies: a higher number corresponded to more frequent use of digital technologies.

#### 3.2.7. Control measures

Previous research pointed out that teaching skills can be affected by seniority (Murnane, 1981). Therefore, as a control variable, we asked participants to report how many years they had been teaching.

### 3.3. Analytics strategy and statistical analysis

We initially ran descriptive statistics, Pearson correlations, and Cronbach's alpha coefficients using SPSS 27. We performed Confirmatory Factor Analyses (CFA) to explore the discriminant validity of all the considered variables using Mplus V.7 (Muthén & Muthén, 2017). To assess the model goodness-of-fit, we used the statistical criteria listed below: Comparative Fit Index (CFI; Bentler, 1990; values above 0.90 are generally treated as indicative of a good model fit; see also Hu & Bentler, 1999), Tucker-Lewis index (TLI; Tucker & Lewis, 1973; values above 0.90 are generally indicated a good model fit), Root Mean Squared Error of Approximation (RMSEA; Steiger, 1990; values <0.08 suggest an adequate model fit) and Standardized Root Mean Square Residual (SRMR; Jöreskog & Sörbom, 1996; values of 0.05 are taken as a good fit, 0.05–0.07 as moderate fit; Brown, 2015). To verify our direct and indirect effects hypotheses, we executed a full structural equation model (SEM), employing Maximum Likelihood as an estimation method, considering the above-reported goodness of fit indices.

### 3.4. Results

#### 3.4.1. Preliminary analysis

Before conducting the primary analyses, data were inspected for normality. Skewness and kurtosis values were all <0.64, indicating a normal distribution for all the variables (Bulmer, 1979) except for the frequency of remote teaching technologies usage (skewness = 1.75; kurtosis = 4.48). Therefore, to address asymmetry, a natural logarithmic transformation was computed (Gelman & Hill, 2006). The transformed index presented a skewness = −1.13 and kurtosis = 1.56, proving a normal distribution of the transformed index (George & Mallery, 2019).

Next, CFAs were carried out to assess the factorial structure of the adopted scales. All CFAs were based on parallel analysis, maximum likelihood, and oblimin rotation.

### 3.4.2. Technostress creators

Analyses suggested a bi-factorial structure of the scale (Bartlett's test of sphericity: $\chi^2(55) = 2356$, $p < .001$; KMO = 0.91). Factor analysis showed loadings higher than 0.538, accounting for 62.4 % of the variance. Because the original validation of the scale (see Molino et al., 2020) suggested a tri-factorial structure, subsequent structural models were computed considering a single latent variable. To reduce the number of parameters to be estimated, we used the partial disaggregation method (Bagozzi & Heatherton, 1994), considering three indicators.

### 3.4.3. PEOU

EFA confirmed a mono-factorial structure of the scale (Bartlett's test of sphericity: $\chi^2(3) = 809$, $p < .001$; KMO = 0.73). Factor analysis showed loadings higher than 0.782, accounting for 81.8 % of the variance.

### 3.4.4. PU

EFAs suggested a mono-factorial structure of the scale (Bartlett's test of sphericity: $\chi^2(3) = 555{,}45$ $p < .001$; KMO = 0.68). Factor analysis showed loadings higher than 0.63, accounting for 74.1 % of the variance.

### 3.4.5. INT

Exploratory factor analyses based on parallel analysis, maximum likelihood, and oblimin rotation suggested a mono-factorial structure of the scale (Bartlett's test of sphericity: $\chi^2(3) = 1096$, $p < .001$; KMO = 0.74) with loadings higher than 0.82, accounting for 86.7 % of the variance.

### 3.4.6. Technical support

Exploratory factor analyses based on parallel analysis, maximum likelihood, and oblimin rotation suggested a mono-factorial structure of the scale (Bartlett's test of sphericity: $\chi^2(3) = 667$, $p < .001$; KMO = 0.72). Factor analysis showed loadings higher than 0.76, accounting for 68.2 % of the variance.

Table 1 included standard deviations, correlations, and Cronbach's alpha values for all the measures. Given the adequate internal consistency, we calculated composite scores for each scale and computed the descriptive statistics. All significant relationships between the variables were in the direction suggested by the previous literature (Table 1).

### 3.4.7. Structural equation models

We first run a confirmatory factor analysis to investigate the discriminant validity of all the six considered latent variables. The CFI, the TLI, the RMSEA, and the SRMR indexes were used to assess the model's goodness-of-fit. All the indexes were adequate (CFI = 0.97; TLI = 0.96, RMSEA = 0.06 (90 % CI 0.05, 0.06), SRMR = 0.05) whereas factor loadings were all between 0.61 and 1.00, thus within the ranges commonly indicated (Brown, 2015).

Therefore, we used Structural Equation Modeling to verify the hypothesized theoretical model (M1; Fig. 1). Findings showed satisfactory fit statistics ($\chi^2(124) = 318.45$, $p < .001$, CFI = 0.96; TLI = 0.95, RMSEA = 0.06, SRMR = 0.06).

### 3.4.8. Competitive models

To assess residual direct effects on the dependent variable not specified in the hypothesized theoretical model (see Fig. 1), we performed formal mediation tests by using nested models. First, a set of $\chi^2$ difference tests were performed (Kline, 2015). Model M1 (Fig. 2) was compared with eight nested models in which we added single direct paths. The chi-square differences revealed no significant additional paths, indicating that M1 fits the data better than other models (Table 3).

### 3.4.9. Tests for direct effects

Supporting HP1, the actual usage of digital technologies for teaching during the pandemic showed a positive relationship with technostress creators ($\gamma = 0.27$, $p < .001$). Confirming HP2a, technostress was directly associated with PEOU ($\gamma = -0.37$, $p < .001$). Nevertheless, and contrary to HP2b, it did not directly affect INT ($p = .80$).

Concerning the key variables of the TAM model, PU ($\gamma = 0.80$, $p < .001$), as well as PEOU ($\gamma = 0.10$, $p = .041$), were both positively and significantly related to INT. Moreover, PEOU was positively associated with PU ($\gamma = 0.13$, $p < .022$). Confirming HP2d, the use of digital technologies during the pandemic significantly predicted PU ($\gamma = 0.17$, $p = .037$).

Contrary to HP3a, we failed to find a significant association of technical support with INT ($p = .96$), whereas, confirming HP3b, it was positively and significantly related to PEOU ($\gamma = 0.17$, $p < .001$). Moreover, confirming HP3d, an association of the technical support with technostress ($\gamma = -0.11$, $p = .047$) was found.

Finally, seniority was negatively and significantly related to PEOU ($\gamma = -0.17$, $p < .001$).

### 3.4.10. Tests for indirect effects

Confirming HP2c, the association between technostress and INT via PEOU was significant ($\beta = -0.036$, $p = .048$; C.I. 95 % = −0.077, −0.010). On the contrary, HP3c was not confirmed as PEOU did not mediate the relationship between perceived technical support and INT ($\beta = -0.017$, $p = .085$; C.I. 95 % = 0.003, 0.038). HP2e was also

**Table 1**
Correlations, means, and standard deviations for the considered variables.

| | α | *M* | *SD* | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 Gender | – | – | – | – | | | | | | |
| 2 Seniority | – | 16.2 | 11.2 | 0.01 | – | | | | | |
| 3 Use of online educational technologies | – | 61.1 | 37.2 | 0.17** | 0.09 | – | | | | |
| 4 Technostress | 0.89 | 2.50 | 0.89 | 0.01 | 0.06 | 0.15** | – | | | |
| 5 Technical support | 0.86 | 3.53 | 1.10 | −0.02 | 0.13** | 0.04 | −0.08 | – | | |
| 6 PU | 0.83 | 3.58 | 0.92 | −0.01 | −0.05 | 0.13* | −0.07 | 0.09* | – | |
| 7 PEOU | 0.89 | 3.64 | 0.91 | −0.08 | −0.14* | 0.01 | −0.42** | 0.17** | 0.12* | – |
| 8 INT | 0.92 | 3.19 | 1.11 | 0.04 | −0.10* | 0.11* | −0.08 | 0.08 | 0.73** | 0.18** |

Note. PEOU = Perceived Ease Of Use; PU = Perceived Usefulness; INT = Intention to use; gender coded as 0 = female; 1 = male.

** $p < .01$.

* $p < .05$.

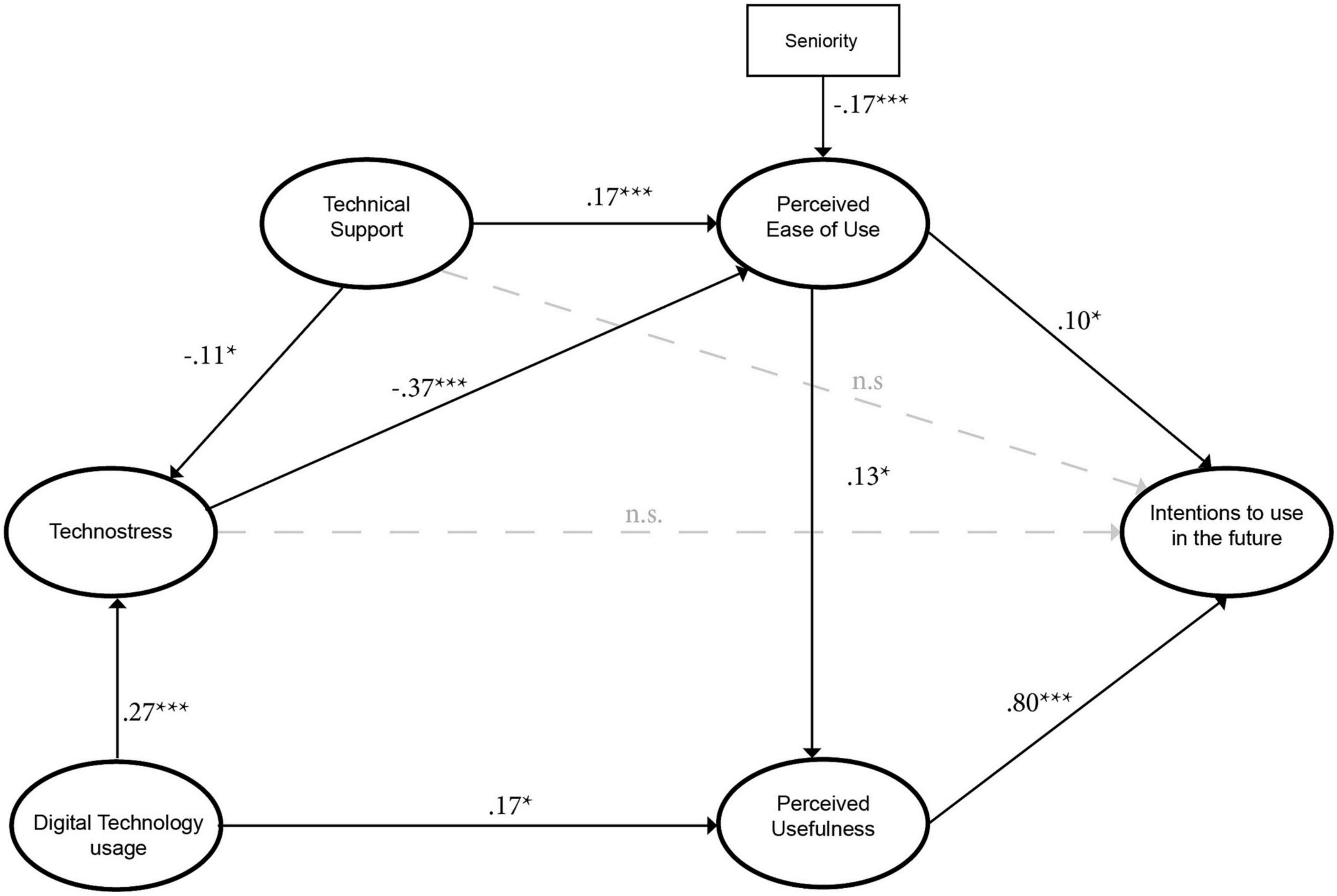


**Fig. 2.** The tested model M1 (ML estimation; standardized path coefficients; $N = 463$). Dashed gray lines indicate nonsignificant relationships. Solid black lines indicate significant relationships. Note. ***$p < .001$;**$p < .01$.*$p < .05$.

confirmed, showing a significant association between technostress and INT, serially mediated by PEOU and PU (β = −0.039, $p = .034$; C.I. 95 % = −0.082, −0.011). Moreover, HP2f was also confirmed; in fact, the actual usage of digital teaching technologies had a significant indirect effect on INT through the mediation of PU (β = 0.136, $p = .040$; C.I. 95 % = 0.054, 0.438). No other significant effects emerged (Table 2). Overall, the tested model accounted for a great amount of variance (67 %) in intentions to use digital technologies for teaching in the future.

## 4. Discussion

In the present work, a sample of university faculty was considered to explore the effects of some of the possible factors that might influence the willingness to adopt digital learning tools after the pandemic by adopting the TAM theoretical framework (Davis & Venkatesh, 1996). From a theoretical perspective, the TAM posits that external factors can positively or negatively influence the intention to adopt new technology in the future. In the present work, among these possible external factors, technostress was considered as an external factor that could have adversely affected digital teaching technology adoption in the future. In contrast, the perception of technical support offered by the university was considered a potential protective factor. One of the main strengths of the present work is that this is one of the few studies that employ an objective measure of past behavior, meant as a possible determinant of the increased stress resulting from the intensive use of digital technologies for teaching.

The frequency of use of digital technologies during the first phase of the pandemic had a direct positive effect on perceived usefulness, indirectly also affecting the intention to continue adopting these technologies in the future (HP2f). To interpret this result, it is crucial to keep in mind the restrictions imposed during the period to which the behavioral data refer. At that time, digital technologies were the only tool available, and as a result, faculty could recognize their usefulness in maintaining teaching activities, favoring their adoption thereafter.

Results also suggested that the actual usage of learning digital technologies during the pandemic was positively associated with technostress creators. We speculate that the sudden changes brought by the pandemic in the teaching sector, which occurred in a very short time, caused high levels of stress. Our findings also suggest that the stressors deriving from the use of digital teaching technologies negatively impacted INT through PEOU (HP2c), supporting the idea that stressors deriving by intense use of digital technologies can create technology-resistance (Chou & Chou, 2021; Joo & Shin, 2020; Kim & Park, 2018), decreasing their perceived ease of use. Such a result is also supported by the significance of the indirect effect of technostress on intentions through the serial mediation of PEOU and PU (HP2e). In this regard, PEOU was also negatively affected by seniority, suggesting that senior faculty perceived digital teaching technologies as more challenging to use. This result can be interpreted based on previous findings, which suggest that age matters for technology use, with older faculty reporting more difficulties in keeping up with new technologies (Meyer & Xu, 2009).

Overall, these results suggest that technostress is a critical variable in determining the use of distance teaching technologies. In this regard, previous studies have already begun to investigate possible variables inhibiting technostress. Among these, organizational support has been found to reduce the effects of technostress (Li & Wang, 2021; Ragu-Nathan et al., 2008). Indeed, our results confirmed this association,

**Table 2**
Tests for indirect effects. Significant indirects effects are marked in bold.

| Indirect effects | Est. | S.E. | p | CI 95 % |
|---|---|---|---|---|
| **Technostress → PEOU → INT (HP2c)** | **−0.036** | **0.02** | ***p* = .048** | **(−0.077, −0.01)** |
| **Technostress → PEOU → PU → INT (HP2e)** | **−0.039** | **0.02** | ***p* = .044** | **(−0.082, −0.011)** |
| Technical support → PEOU → INT (HP3c) | 0.017 | 0.01 | *p* = .085 | (0.003, 0.038) |
| Technical support → PEOU → PU → INT (HP3e) | 0.018 | 0.01 | *p* = .068 | (0.000, 0.011) |
| Technical support → Technostress → INT | −0.001 | 0.005 | *p* = .82 | (−0.011, 0.008) |
| Technical support → Technostress → PEOU → INT | 0.004 | 0.003 | *p* = .173 | (0.000, 0.011) |
| Technical support → Technostress → PEOU → PU → INT | 0.004 | 0.003 | *p* = .178 | (0.000, 0.012) |
| Seniority → PEOU → INT | −0.017 | 0.011 | *p* = .118 | (0.000, 0.000) |
| Seniority → PEOU → PU → INT | −0.018 | 0.010 | *p* = .083 | (0.000, 0.000) |
| **Use of Online Educational Technologies → PU → INT (HP2f)** | **0.136** | **0.066** | ***p* = .040** | **(0.054, 0.438)** |
| Use of Online Educational Technologies → Technostress → INT | 0.003 | 0.011 | *p* = .806 | (−0.03, 0.037) |
| Use of Online Educational Technologies → Technostress → PEOU → INT | −0.01 | 0.005 | *p* = .081 | (−0.038, −0.002) |
| Use of Online Educational Technologies → Technostress → PEOU→PU → INT | −0.01 | 0.006 | *p* = .082 | (−0.040, −0.003) |

Note. PEOU = Perceived Ease Of Use; PU = Perceived Usefulness; INT = Intention to use.

showing that organizational support can function as a protective factor concerning stress arising from using technology in organizational settings. We speculate that the perception of having technical support can help users both technically and with respect to the functionality offered by digital tools, as indicated by previous studies showing that having adequate organizational support can lead to lower job stress (Asad & Khan, 2003). This is even more relevant in emergencies - such as the COVID-19 pandemic – in which the perception of organizational support can improve individuals' perception of control over work and life (Thomas & Ganster, 1995). The perception of having a reference point in handling technical difficulties might have also promoted a greater perception of ease of use. This could stem from the fact that, during the pandemic emergency, the technical support offered by the university might have been perceived as a guide in understanding new and scarcely before adopted tools, thus contributing to a greater understanding of how these technologies work, thereby reducing uncertainty in their use.

Like all studies, the present work has limitations. First, we could not detect the actual use of technologies once the pandemic emergency subsided and classes returned to attendance, for example, by adopting a longitudinal design. This limitation stemmed mainly from the fact that in the months following the acute phase of the pandemic, classes and academic activities maintained a dual mode (online and offline), making it impossible to obtain clean behavioral data. Second, only some specific distance teaching technologies were considered, while faculty involved in the study may have also used other technologies besides those provided by the university.

Third, during the ongoing COVID-19 pandemic, other stressors (e.g., the inability to leave home or the availability of adequate space to work from home) may have influenced PU and PEOU of remote teaching technologies, indirectly affecting the intentions to integrate them in future teaching activities. Fourth, for privacy reasons, it was not possible to detect whether participants had contracted the disease during the survey period, thus leading to additional stressors (e.g., pandemic fatigue, see Reicher & Drury, 2021). Furthermore, as the data collection was conducted during the COVID-19 emergency period, the results obtained may not be generalizable to future transitions to online teaching options. Therefore, further studies should consider additional external factors that might negatively influence the intentions to integrate digital educational technologies into future teaching practice. Likewise, additional variables that can mitigate the effects of technostress (e.g., perceived control, self-efficacy) should be investigated. The present study also has several strengths. First, it provides a broader understanding of the factors that may influence university professors' future use of educational technologies, even after the end of the COVID-19 pandemic. Understanding these variables is crucial for designing future interventions aimed at incorporating and consolidating the use of instructional technologies in academic teaching processes. In addition, the present study made it possible to integrate one of the new psychosocial risk factors, namely technostress, into investigating factors influencing the use of new technologies. Over the years, TAM has been integrated in various ways; however, emotional and personal variables (Taherdoost, 2019), which allow for greater understanding and prediction of future adoption behaviors, always remain missing.

## 5. Conclusion

The COVID-19 pandemic has led to a revolution in academic instruction (Nuere & De Miguel, 2021). Especially during the most acute phase of the pandemic, most governments worldwide have temporarily closed educational institutions to contain the spread of the COVID-19 disease (UNESCO, 2020). The teaching methods used by academic institutions had to be revised to embrace digital technology, some of them for the first time (Singh et al., 2021). In this respect, universities have proven to be the more resilient institutions. Within a few days, universities around the globe were promptly using already available digital tools or activating new ones not to suspend their teaching programs (Dwidienawati et al., 2020).

Although these initiatives have brought benefits (e.g., the continuation of classes and school careers), the massive and coercive use of digital technologies for teaching has also caused negative consequences, such as increased anxiety, negative affect, and stress (Toto & Limone, 2021) in both students and teachers. Considering this perspective, we

**Table 3**
Tests for competitive models. *** = p<.001.

| Models | Added path | $\chi^2$ | *df* | CFI | TLI | RMSEA | SRMR | Comparison | $\Delta\chi^2(1)$ |
|---|---|---|---|---|---|---|---|---|---|
| M1 | – | 318.45*** | 124 | 0.95 | 0.94 | 0.06 | 0.06 | – | – |
| M2 | Technostress → PU | 317.57*** | 123 | 0.95 | 0.94 | 0.06 | 0.06 | $M_1 – M_2$ | 0.88 n.s. |
| M3 | Technical Support → PU | 317.73*** | 123 | 0.96 | 0.94 | 0.06 | 0.06 | $M_1 – M_3$ | 0.72 n.s. |
| M4 | Seniority → PU | 316.26*** | 123 | 0.96 | 0.94 | 0.06 | 0.06 | $M_1 – M_4$ | 2.19 n.s. |
| M5 | Seniority → INT | 316.10*** | 123 | 0.96 | 0.94 | 0.06 | 0.06 | $M_1 – M_5$ | 2.35 n.s. |
| M6 | Seniority → Technostress | 318.45*** | 123 | 0.96 | 0.94 | 0.06 | 0.06 | $M_1 – M_6$ | 0.00 n.s. |
| M7 | Use of Online Educational Technologies → Technical. Support | 318.45*** | 123 | 0.96 | 0.94 | 0.06 | 0.06 | $M_1 – M_7$ | 0.00 n.s. |
| M8 | Use of Online Educational Technologies → PEOU | 314.98*** | 123 | 0.96 | 0.95 | 0.06 | 0.06 | $M_1 – M_8$ | 3.47 n.s. |
| M9 | Use of Online Educational Technologies → INT | 318.28*** | 123 | 0.96 | 0.94 | 0.06 | 0.06 | $M_1 – M_9$ | 0.17 n.s. |

Note. PEOU = Perceived Ease Of Use; PU = Perceived Usefulness; INT = Intention to use.

speculated that the changes resulting from the COVID-19 pandemic were not all bad for the education sector. Especially during the first year of the current COVID-19 pandemic, technologies were the only way to maintain meaningful social relationships (Gabbiadini et al., 2019; Pancani et al., 2021). Similarly, in education, digital technologies have enabled new teaching practices causing a deep change in the professional modality of teachers (Toto & Limone, 2021) and, possibly, new ways of relating to students. As Waytz and Gray (2018) suggested, digital technologies can improve social relationships when close offline relationships are unavailable.

Similarly, digital technologies for remote teaching have been crucial to the maintenance of educational activities within universities. In addition, the rapid digitization driven by Covid-19 has allowed for the renewal of teaching strategies, incorporating new innovative tools. However, the psychological cost of intensive use of such technologies (e.g., technostress) may have led to underestimate the possible benefits that digital technologies can bring to daily teaching practice. The present study suggests that to avoid this possibility, organizational support is critical in mitigating the effects of stressors resulting from the intensive use of such technologies, thereby fostering individuals to identify the benefits and the new possibilities such tools can bring. In this regard, we suggest that an appropriate organizational atmosphere and welfare mechanism is meaningful in alleviating employees' technostress and role stress.

It is therefore essential for organizations, whether public or private, to identify in advance the disruption scenarios that may occur and assess their impact. Consequently, they will need to plan responses that can ensure continuity, offering adequate technical, operational, and psychological support to their employees. In this way, the possible stress resulting from the event can be quickly transformed into techno-eustress (Tarafdar et al., 2019), thus activating coping behaviors to master the challenges in a positive way and achieve positive outcomes.

Due to technology's increasingly central role in society, preparing future teachers with adequate technology skill proficiency is also important (Northrup & Little, 1996). Nevertheless, teacher technology skills alone are not enough to facilitate the integration of digital learning tools into teaching practices (Vannatta & Beyerbach, 2000). It is therefore important that designers, psychologists, and developers work together to design tools that are easy to use and that consider, even in the early design stage, the human factors involved in their use.

Such technologies should also be increasingly inclusive. Indeed, while universities have been less affected by teaching disruptions, this has not been the case – at least in Italy - for the lower teaching grades. Therefore, institutions and policymakers must implement digital education policies so that the next generation of students can enjoy a richer education system.

Future studies should investigate how to design proper and practical tools for investigating motivation and perceived stress in relation to digital teaching technologies, promoting positive changes in the world of education. Furthermore, it is necessary to develop interventions and prevention models in relation to the stress perceived by teachers, leading to greater psychological well-being for both teachers and students. It is of primary importance for the education system and the public institutions to capitalize on what the world has faced during the COVID-19 pandemic, making sure that what happened can lead to positive changes for all of society by providing advanced forms of teaching that are accessible to everyone and promoting positive changes in the world of education.

## Ethics approval statement

All procedures performed in the present study were in accordance with the APA ethical guidelines and the ethical principle of the “Helsinki Declaration” and the Oviedo Convention on human rights and biomedicine. Data were collected after obtaining consent from the University Data Protection Office of the University of Milano-Bicocca.

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## Declaration of competing interest

No potential competing interest are reported by the authors.

## Data availability

Data will be made available on request.

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