Technostress and Remote Work: Understanding Underlying Factors of Role Ambiguity

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Abstract

Considering the possible impacts of technostress on individuals and organizations and the remote work regime imposed on education employees during the pandemic that intensified the use of technologies, the aim of this paper was to analyze underlying factors related to role ambiguity, their effects and forms of mitigation. The final sample is comprised of 691 complete responses. The data were collected electronically between August, 2021 and November, 2021. To test the study hypotheses, we adopted the Structural Equation Modeling. According to the main results, Computer Self-Efficacy can mitigate the effects of Role Ambiguity and, indirectly, Computer Self-Efficacy also has a negative effect on Cognitive Load. We also observed that Role Ambiguity presented a positive effect on Cognitive Load. The variable Resilience moderated the relationships: i) between Computer Self-Efficacy and Role Ambiguity; and ii) between Role Ambiguity and Cognitive Load.

Keywords: Remote work; Self-Efficacy; Covid-19; Technostress; Resilience.

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1. Introduction

Since COVID-19 emerged in Wuhan, China, in late 2019, the pandemic has spread across the world, causing millions of deaths and transforming the lives of billions of people (Harunavamwe & Ward, 2022). Besides the impact on public health, the crisis also affected the educational sector, leading to difficulties in maintaining its activities (Aktan & Toraman, 2022). Consequently, institutions have made significant changes in the way they offer their services and in the way their employees develop their working activities (Aktan & Toraman, 2022; Procentese et al., 2023). Without previous planning, teachers needed to adapt to the use of information technologies to teach and interact with students, a factor that affected their professional performance, their health and personal lives (Aktan & Toraman, 2022; Arslan et al., 2022; Lizana et al., 2021; Molino et al., 2020).

Even though the pandemic situation is currently under control, the pandemic has brought a new "normal" to the reality of individuals and organizations (Singh et al., 2022). As a learning experience, remote work presented itself as an interesting means of working due to its practicality and low cost, and continues to be used by universities and many organizations (Anh et al., 2023; Harunavamwe & Ward, 2022; Hurbean et al., 2022; Singh et al., 2022). In the universities, many working activities such as meetings between members of academic and administrative units and guidance for students in undergraduate and postgraduate programs often continue to be carried out remotely. This scenario also indicates a trend towards greater adoption of remote work tools in the future.

Remote work involves the use of a variety of technological resources and digital platforms, such as: internet, wireless networks, computers, smartphones and software (Riedl, 2022). The literature shows that although technologies can bring benefits such as increased productivity and reduced costs to organizations, the way that they are inserted, as well as the way in which technologies are perceived by professionals, can cause undesirable effects (Califf & Brooks, 2020; Lei & Ngai, 2014; Ragu-Nathan et al., 2008; Tarafdar et al., 2007).

Previous studies suggest a high incidence of problems associated with the intensive use of technologies by people of all countries, ages, genders and cultures (Li & Wang, 2021; Ma & Turel, 2019). The interaction between individuals and technological demands can generate stress caused by the use of technology, which is also known as Technostress (Ragu-Nathan et al., 2008; Tarafdar et al., 2007, 2019).

In the literature on technostress, different types of techno-stressors have been identified. Techno-stressors can be understood as events generated by the use of technologies that cause some type of perception and reaction in the user (Dragano & Lunau, 2020). The use of technology enables, for example, multitasking, creating role ambiguity that can be defined as indecision about which task or work the individual should perform (Ayyagari et al., 2011). Constantly changes in tasks, in turn, can increase cognitive load, leading the individual to exhaustion (Luqman et al., 2021; Wang et al., 2023). On the other hand, the literature shows that individual characteristics, such as resilience and self-efficacy, are capable of mitigating the levels of technostress and its effects (Cappellozza et al., 2019; Chou & Chou, 2021; Oksanen et al., 2021; Singh et al., 2022; Yener et al., 2021).

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In this context, considering the possible impacts of technostress on individuals and organizations and the remote work regime imposed on education employees during the pandemic that intensified the use of technologies, **the aim of this paper was to analyze underling factors related to role ambiguity, their effects and forms of mitigation**. Therefore, the research question that guided this study was: what are the factors underlying role ambiguity during remote work?

To the best of our knowledge, this is the first study that investigates the relationship between self-efficacy, role ambiguity and cognitive load among education professionals. Furthermore, this research also aims to expand studies on the relationship between resilience and technostress. It is worth mentioning that, in this research, these relationships were explored in an unprecedented context, as it addresses a pandemic situation and considers education professionals who, for the most part, had never worked remotely before.

2. Research Model and Study Hypotheses

Individuals tend to avoid situations based on their belief that such situations could require abilities that they do not dominate, but, on the other hand, individuals can feel comfortable in developing activities related to abilities that they think dominate (Bandura, 1978). This reasoning is related to the perception of self-efficacy (Bandura, 1978), a construct that can be measured in different areas (Durndell et al., 2000). Computer self-efficacy refers to the belief of an individual on their own abilities to execute actions or specific tasks involving computers (Durndell et al., 2000; Karsten et al., 2012). The use of new systems can be, by itself, stressful (Sasidharan, 2022). When employees have to use technology more intensively, and when the use of technology involves their connection with other employees, customers or superiors, this intensity can create a sense of limited freedom, having the potential to increase the levels of stress (Delpechitre et al., 2019).

Moreover, technology change contributes to the development of new resources, which also demand new capabilities (Delpechitre et al., 2019). Therefore, technological innovations, new software and applications can facilitate the activities developed by employees, but also create a need for additional time to dedicate in training and updating, a factor that also can increase technostress. When technological resources used by the companies change frequently, employees need to invest time and efforts to efficiently use these resources and develop their work (Suh & Lee, 2017). Therefore, this additional effort in understanding and using new technological resources can create a conflict of what activity to do first (Suh & Lee, 2017): learn about technology or develop the regular work. Computer self-efficacy can mitigate this conflict, as individuals who believe that they have the necessary abilities to effectively use technology can dedicate more time in perform their regular work. Therefore, the first hypothesis of the study is:

H1: Computer Self-Efficacy has a negative effect on Role Ambiguity.

When individuals employ technologies to develop their daily work, some mental processes take place and cognitive load is among them (Ortiz De Guinea et al., 2013). Cognitive load is related to a limited capability that individuals have in receiving and processing different amounts of information (Miller, 1956; Ortiz De Guinea et al., 2013). Cognitive load theory aims to assist the assimilation of information, optimizing intellectual performance (Sweller et al., 1998). The theory involves long-term and working memories, as well as their characteristics (Duran et al., 2022). Since humans have limited capability handle large amounts of information, there are alternatives that can assist in the interaction with information.

If the work developed by employees requires a higher level of attention, making task transitions can present a negative effect on such level of attention (Luqman et al., 2021). As Role Ambiguity is a type of role stress (Delpechitre et al., 2019) and refers to conflicts in developing different tasks (Suh & Lee, 2017), we argue that an intense level of task changes can also increase the Cognitive Load of employees. In the case of this paper, Role Ambiguity refers to changes among regular work and technological tasks, especially due the new requirements imposed by remote work in the context of COVID-19. Therefore, the second hypothesis of the study is:

H2: Role Ambiguity has a positive effect on Cognitive Load.

Previous studies suggest that individual resilience is a form of psychological and emotional control for individuals in the face of a stressful process (Oksanen et al., 2021; Pflügner et al., 2021; Pirkkalainen et al., 2019; Reynolds et al., 2022; Singh et al., 2022; Tuan, 2022; Wagnild & Young, 1993). Resilience can be defined as "a dynamic process encompassing positive adaptation within the context of significant adversity" (Luthar et al., 2000, p.543). Resilient people tend to be flexible to new technologies adoption and tend to overcome technological setbacks or difficulties, not transferring the effect of one experience to another (Magotra et al., 2016). In this way, resilience is an essential element for any worker to adapt to new technologies available at work (Cappellozza et al., 2019).

Discrepancies found regarding worker resilience during the COVID-19 pandemic suggest the need for organizational support for those who lack resilience at work (Oksanen et al., 2021). Pflügner et al., (2021) point that individuals with greater level of resilience evaluate situations related to technology less frequently as threatening and, in some cases, begin to perceive them as challenging. In this way, perceiving control over a given stressful situation is directly linked to high levels of individual resilience (Pirkkalainen et al., 2019; Tuan, 2022).

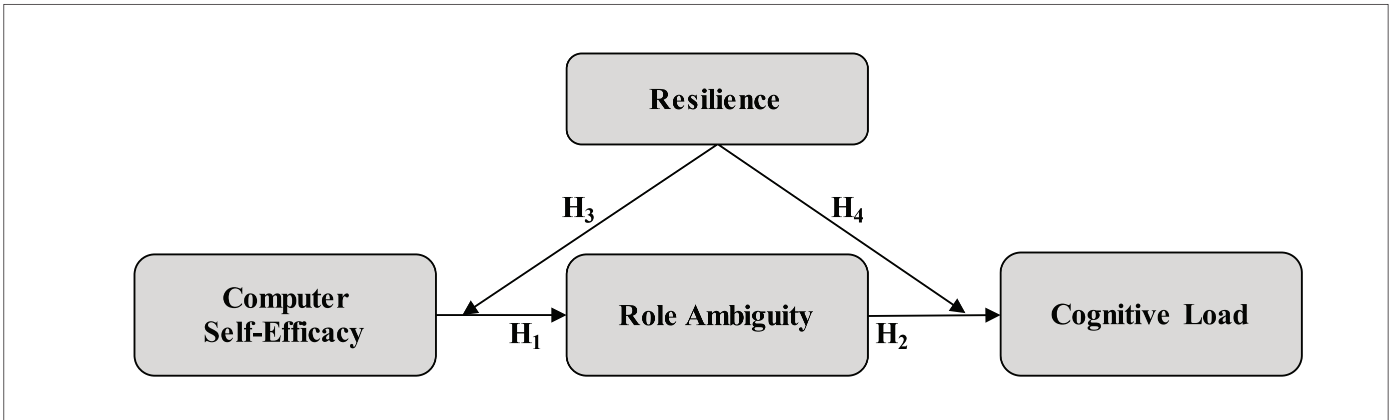
Singh et al. (2022) found that resilience can moderate the effect of techno-exhaustion on well-being and Cappellozza et al. (2019) indicate that resilience is capable of mitigating the effects of techno-invasion on work-family conflict. Furthermore, the study of Rushton et al. (2015) shows that resilience protects individuals from emotional exhaustion at the work environment. In sum, resilience helps individuals to keep a high sense of well-being and to maintain their physical and psychological health by mitigating the negative effects triggered by periods of crisis (Aguiar-Quintana et al., 2021). Considering the reasoning presented above, we argue that resilience allows workers to overcome difficulties related to the use of technologies, mitigating the impact of significant sources of stress present at work. Therefore, the following research hypotheses are proposed:

H3: Resilience moderates the effect of Computer Self-Efficacy on Role Ambiguity.

H4: Resilience moderates the effect of Role Ambiguity on Cognitive Load.

Figure 1. summarizes the research model of this paper.

Figure 1: Research Model



3. Data and Methods

The research questionnaire was developed based on previous studies (Delpechitre et al., 2019; Durndell et al., 2000; Ortiz De Guinea et al., 2013; Suh & Lee, 2017; Wagnild & Young, 1993). Each construct was derived from different references, as shown in Appendix A. Considering that the questionnaire directly involves the context of the COVID-19 pandemic, some minor textual adjustments were applied to the original items (Appendix A shows the final version). The questionnaire items were translated into Brazilian Portuguese, the local language of the respondents. Before data collection, the translated version was evaluated by a professor experienced in publishing papers in international journals in the field of information systems research. All questions were answered using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The final sample is comprised of 691 complete responses. Table 1 contains descriptive statistics for the main constructs of the paper.

Table 1: Descriptive statistics for the main constructs

Construct	n	Mean	S.D.	Min.	Max.
Role Ambiguity	691	2.594	0.993	1.000	5.000
Computer Self-Efficacy	691	3.309	0.987	1.000	5.000
Cognitive Load	691	3.965	0.871	1.000	5.000
Resilience	691	3.619	0.591	1.000	5.000

Notes: to generate this table with descriptive statistics, we first calculated the average score that each respondent assigned to the questions within each construct; next, we computed the descriptive statistics based on these average scores for each construct.

The responses were collected electronically between August, 2021 and November, 2021. It is important to highlight that the majority of the respondents were developing their activities remotely due the COVID-19 restrictions. The responses were anonymous, and participation was completely voluntary. The research protocol was previously approved by the Ethical Committee of the university to which the authors are affiliated.

Before testing the study hypotheses, we assessed the convergent and discriminant validity of the constructs (Anderson & Gerbing, 1988). For convergent validity, we observed the following indicators (Bagozzi & Yi, 2012; Hair et al., 2017): Cronbach's Alpha (CA), that was expected to be equal or greater than 0.70, Composite Reliability (CR) that was expected to be equal or greater than 0.70, and Average Variance Extracted (AVE) that was expected to be equal or greater than 0.50. Regarding discriminant validity, we compared the correlation between each pair of constructs with the root square of its own AVE (Fornell & Larcker, 1981); a concern would rise when the correlation between the constructs is greater than the square root of the AVE of the respective construct (Hair et al., 2017).

We also used the heterotrait-monotrait ratio (HTMT) criterion to access discriminant validity (Hair et al., 2017; Henseler et al., 2015). To test the study hypotheses, we adopted the Structural Equation Modeling (SEM). It is important to note that two hypotheses of the quantitative model involve a multi-group comparison (H3 and H4). Therefore, based on the average scores of the items for the construct resilience, we segregated the study sample into two groups based on a threshold of 3.5: a sub-sample with high values for resilience (n=428) and another with low values for resilience (n=263). We then estimated the research model for each sub-sample and saved the coefficients and the respective standard errors. Following previous literature (Hwang, 2010; Keil et al., 2000), we employed the procedure suggested by Wynne Chin to compare the path coefficients obtained in each sub-group of analysis.

4. Results

4.1 Convergent and Discriminant Analysis

The first step of the quantitative analysis in this paper was the evaluation of convergent validity. The constructs in Table 2 showed good indexes for Composite Reliability and Cronbach's Alpha, with values above 0.80. Similarly, the results showed good fit in relation to AVE, with values above 0.60 (as reported in Table 2).

Table 2: Results for Convergent Analysis

Construct	Av. Var. Ext.	Comp. Rel.	Cronb. Alpha
Role Ambiguity	0.730	0.890	0.883
Computer Self-Efficacy	0.659	0.852	0.846
Cognitive Load	0.757	0.903	0.899

Table 3 presents the results for discriminant validity considering the comparison of the correlation between each pair of constructs with the root square of its own AVE (Fornell & Larcker, 1981). All the values in bold on the diagonal were higher than the correlations between each pair of constructs, indicating good fit for discriminant validity.

Table 3: Results for Discriminant Analysis

Construct	Role Ambiguity	Computer Self-Efficacy	Cognitive Load
Role Ambiguity	**0.854**		
Computer Self-Efficacy	-0.322	**0.812**	
Cognitive Load	0.437	-0.003	**0.870**

Notes: the values in bold on the diagonal represent the root square of the AVE for the respective construct; the values below the diagonal indicate the correlation between each pair of constructs.

We also used an alternative procedure to access discriminant validity, based on the HTMT criterion. Table 4 contains the results. In the same line of the results observed in Table 3, these constructs did not present concerns related to discriminant validity, as the highest coefficient was 0.473, which is below the threshold of 0.90 indicated by literature (Hair et al., 2017; Henseler et al., 2015).

Table 4: Results for Discriminant Analysis (HTMT criterion)

Construct	Role Ambiguity	Computer Self-Efficacy	Cognitive Load
Role Ambiguity			
Computer Self-Efficacy	0.334		
Cognitive Load	0.473	0.021	

In relation to the goodness of fit of the quantitative model, the following results were observed: Comparative Fit Index (CFI) = 0.985; Root Mean Square Error of Approximation (RMSEA) = 0.058 (the lower bond was 0.044); Qui-Square Statistic = 80.1 (24 degrees of freedom); Tucker Lewis Index (TLI) = 0.977. These indicator values show good adjustments for this stage of confirmatory factor analysis. The next step was to evaluate the study hypotheses.

4.1 Hypotheses Testing

In order to analyze the research model, we first evaluated the proposed relationships of H1 and H2, and Table 5 contains the main results. We observed a negative effect of Computer Self-Efficacy on Role Ambiguity, an evidence that supports H1. Therefore, individuals that present higher levels for Computer Self-Efficacy tend to present lower levels for Role Ambiguity. In relation to H2, it was also supported, since the results indicate a positive effect of Role Ambiguity on Cognitive Load. Individuals perceiving high levels of Role Ambiguity tend to suffer more with Cognitive Load factors.

Table 5: Results for the relationships proposed in H1 and H2

Relationship			Coef.	Sig.
Comp. Self-Efficacy	--->	Role Ambiguity	-0.318	***
Role Ambiguity	--->	Cognitive Load	0.431	***

Notes: number of responses = 691; r-squared for Role Ambiguity = 10.1%; r-squared for Cognitive Load = 18.6%.

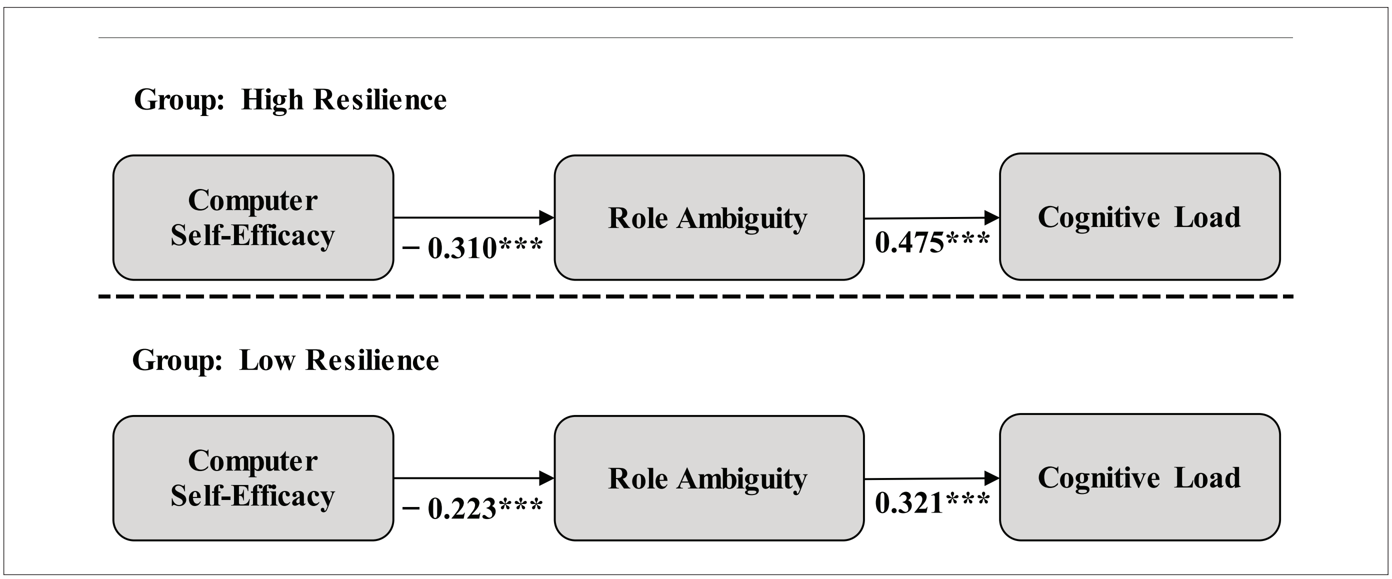
Complementarily, using a bootstrap procedure (number of bootstrap samples = 1,000), we tested the indirect effect of Computer Self-Efficacy on Cognitive Load. The result indicated a coefficient of -0.154 (significant at 1%). This result for the indirect effect suggests that Computer Self-Efficacy can help in reducing the effects of Role Ambiguity and, indirectly, it also can mitigate Cognitive Load (since the coefficient was negative and statistically significant). Table 6 contains the results considering the entire research model; Figure 2 illustrates the moderating effect among the two groups of analysis.

Table 6: Results considering the moderating role of the variable Resilience

Relationship			High Resiliene		Low Resiliene		Difference	
			Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
Comp. Self-Efficacy	--->	Role Ambiguity	-0.310	***	-0.223	***	-0.087	***
Role Ambiguity	--->	Cognitive Load	0.475	***	0.321	***	0.154	***

Notes: as explained in the methods section, based on the average scores of the items for the construct resilience, we segregated the study sample into two groups based on a threshold of 3.5: a sub-sample with high values for resilience (n=428) and another with low values for resilience (n=263). We then estimated the research model for each sub-sample.

Figure 2: The moderating role of Resilience



Based on the entire research model (Table 6), the main results of the paper supports H1, since Computer Self-Efficacy presented a negative effect on Role Ambiguity. Respondents that presented higher levels of Computer Self-Efficacy tended to show lower levels of Role Ambiguity. This result is in line with our argument that Computer Self-Efficacy can mitigate the conflict of what activity to do first (Suh & Lee, 2017): learn new technological functions or do the regular work. Since technological changes can require new capabilities (Delpechitre et al., 2019), the context of COVID-19 Pandemic required of many employees the use of technology to perform their tasks, even if they are not familiar with technology.

Our findings also suggest a positive effect of Role Ambiguity on Cognitive Load, which supports H2. Therefore, when employees need to change tasks constantly, particularly changing among technological tasks and regular work, they tend to present higher levels for Cognitive Load, an outcome of Technostress.

Resilience also showed an important construct in this paper, since it presented a moderating effect, supporting H3 and H4. In line with previous studies (Oksanen et al., 2021; Pflügner et al., 2021; Pirkkalainen et al., 2019; Singh et al., 2022; Tuan, 2022; Wagnild & Young, 1993), such result reinforces the importance of Resilience to face stressful process, particularly in the case of H3. The result is also in line with previous research (Pflügner et al., 2021) about how Resilience can contribute to reduce the negative effects of threatening situations related to technology.

As shown in Table 6 and Figure 2, individuals exhibiting elevated levels of Resilience demonstrated a more pronounced negative effect of Computer Self-Efficacy on Role Ambiguity. These findings suggest that individuals exhibiting higher levels of Resilience and higher levels of Computer Self-Efficacy tend to experience lower levels of Role Ambiguity. Conversely, the effect of Role Ambiguity on Cognitive Load was more pronounced among the sub-sample with higher levels of Resilience. This result indicates that the consequences of Role Ambiguity on Cognitive Load tend to be more pronounced among individuals with higher levels of Resilience.

5. Conclusion

The use of technology in the organizational environment has many benefits but it also creates some challenges. In the context of universities, as a response to the restrictions imposed by the COVID-19 pandemic, teachers and administrative employees needed to develop their activities using tools for remote work. Therefore, they were required to interact with information technology to make their regular work. However, as previously presented, the use of technology can bring undesirable effects for individuals (Califf & Brooks, 2020; Lei & Ngai, 2014; Ragu-Nathan et al., 2008; Tarafdar et al., 2007).

Considering this context, the aim of this paper was to analyze underling factors related to role ambiguity, their effects and forms of mitigation. The main results indicated that Computer Self-Efficacy can mitigate the effects of Role Ambiguity and, indirectly, Computer Self-Efficacy also has a negative effect on Cognitive Load. We also observed that Role Ambiguity presented a positive effect on Cognitive Load. The variable Resilience moderated the relationships: i) between Computer Self-Efficacy and Role Ambiguity; and ii) between Role Ambiguity and Cognitive Load.

By addressing the relationships between Self-Efficacy, Role Ambiguity and Cognitive Load in the context of universities, this paper presents an important contribution to facilitate the management of educational institutions. When technological resources are imposed, their use can negatively affect the activities developed by teachers and the administrative staff, creating barriers to the performance of these employees and also having the potential to affect the learning environment.

The activities usually carried out by teachers involve a level of multitasking. Therefore, when teachers must combine the demands of regular work with those of technological resources, this can create additional levels of stress. In this scenario, when educational institutions are required to implement new technological resources, they can collect employees' feedback regarding these technologies and offer more training and support options to mitigate the effects of multitasking.

Moreover, the results of this research suggest that computer self-efficacy plays an important role in mitigating the effects of role ambiguity and, indirectly, cognitive load. With this result in mind, educational institutions can encourage teachers and administrative staff to participate in courses on new technologies. Such participation can gradually enhance their ability to interact with contemporary resources, facilitating the adoption of new technologies by the employees when an external situation is suddenly imposed on universities (as occurred during the COVID-19 pandemic).

The context in which this research was developed, using a database collected during a period of remote work due to pandemic limitations, highlights an unprecedented panorama for testing the study's hypotheses. As mentioned in the introduction of this paper, many respondents had never used before some of the technologies required for remote work.

This paper has some limitations. The first limitation is related to sample composition, since it was not adopted some random criteria to select respondents. We expect that the relatively large number of respondents (n = 691) attenuates this limitation. Another limitation is related to the number of antecedents considered in the research model. Therefore, further research can consider the main results of this paper and expand the research model by including new antecedents for technostress.

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References

Aguiar-Quintana, T., Nguyen, H., Araujo-Cabrera, Y., & Sanabria-Díaz, J. M. (2021). Do job insecurity, anxiety and depression caused by the COVID-19 pandemic influence hotel employees' self-rated task performance? The moderating role of employee resilience. *International Journal of Hospitality Management,* 94, 102868. https://doi.org/10.1016/j.ijhm.2021.102868

Aktan, O., & Toraman, Ç. (2022). The relationship between Technostress levels and job satisfaction of Teachers within the COVID-19 period. *Education and Information Technologies*, *27*(7), 10429–10453. https://doi.org/10.1007/s10639-022-11027-2

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Anh, L. E. T., Whelan, E., & Umair, A. (2023). 'You're still on mute'. A study of video conferencing fatigue during the COVID-19 pandemic from a technostress perspective. *Behaviour & Information Technology*, *42*(11), 1758–1772. https://doi.org/10.1080/0144929X.2022.2095304

Arslan, H., Şahin, Y. L., Ferhan Odabaşı, H., & Okur, M. R. (2022). An investigation of change in teachers' technostress levels before and after the Covid-19 outbreak. *Educational Media International*, *59*(2), 95–111. https://doi.org/10.1080/09523987.2022.2101202

Ayyagari, Grover, & Purvis. (2011). Technostress: Technological Antecedents and Implications. *MIS Quarterly*, *35*(4), 831. https://doi.org/10.2307/41409963

Bagozzi, R. P., & Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. *Journal of the Academy of Marketing Science*, *40*(1), 8–34. https://doi.org/10.1007/s11747-011-0278-x

Bandura, A. (1978). Self-efficacy: Toward a unifying theory of behavioral change. *Advances in Behaviour Research and Therapy*, *1*(4), 139–161. https://doi.org/10.1016/0146-6402(78)90002-4

Califf, C. B., & Brooks, S. (2020). An empirical study of techno-stressors, literacy facilitation, burnout, and turnover intention as experienced by K-12 teachers. *Computers & Education*, *157*, 103971. https://doi.org/10.1016/j.compedu.2020.103971

Cappellozza, A., Ferreira, A. S., & Loyola, L. C. M. (2019). Relations between Technostress, Resilience and Work-Family Conflict. *Latin American and Caribbean Journal of the Association for Information Systems*, *11*(2), 1–15.

Chou, H.-L., & Chou, C. (2021). A multigroup analysis of factors underlying teachers' technostress and their continuance intention toward online teaching. *Computers & Education*, *175*, 104335. https://doi.org/10.1016/j.compedu.2021.104335

Delpechitre, D., Black, H. G., & Farrish, J. (2019). The dark side of technology: Examining the impact of technology overload on salespeople. *Journal of Business & Industrial Marketing*, *34*(2), 317–337. https://doi.org/10.1108/JBIM-03-2017-0057

Dragano, N., & Lunau, T. (2020). Technostress at work and mental health: Concepts and research results. *Current Opinion in Psychiatry*, *33*(4), 407–413. https://doi.org/10.1097/YCO.0000000000000613

Duran, R., Zavgorodniaia, A., & Sorva, J. (2022). Cognitive Load Theory in Computing Education Research: A Review. *ACM Transactions on Computing Education*, *22*(4), 1–27. https://doi.org/10.1145/3483843

Durndell, A., Haag, Z., & Laithwaite, H. (2000). Computer self efficacy and gender: A cross cultural study of Scotland and Romania. *Personality and Individual Differences*, *28*(6), 1037–1044. https://doi.org/10.1016/S0191-8869(99)00155-5

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd Edition). Los Angeles (USA): Sage publications.

Harunavamwe, M., & Ward, C. (2022). The influence of technostress, work–family conflict, and perceived organisational support on workplace flourishing amidst COVID-19. *Frontiers in Psychology*, *13*, 921211. https://doi.org/10.3389/fpsyg.2022.921211

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hurbean, L., Dospinescu, O., Munteanu, V., & Danaiata, D. (2022). Effects of Instant Messaging Related Technostress on Work Performance and Well-Being. *Electronics*, *11*(16), 2535. https://doi.org/10.3390/electronics11162535

Hwang, Y. (2010). The moderating effects of gender on e-commerce systems adoption factors: An empirical investigation. *Computers in Human Behavior*, *26*(6), 1753–1760. https://doi.org/10.1016/j.chb.2010.07.002

Karsten, R., Mitra, A., & Schmidt, D. (2012). Computer Self-Efficacy: A Meta-Analysis. *Journal of Organizational and End User Computing*, *24*(4), 54–80. https://doi.org/10.4018/joeuc.2012100104

Keil, M., Tan, B. C. Y., Wei, K.-K., Saarinen, T., Tuunainen, V., & Wassenaar, A. (2000). A Cross-Cultural Study on Escalation of Commitment Behavior in Software Projects. *MIS Quarterly*, *24*(2), 299. https://doi.org/10.2307/3250940

Lei, C. F., & Ngai, E. W. T. (2014). The double-edged nature of technostress on work performance: A research model and research agenda. *Thirty Fifth International Conference on Information Systems, Auckland.*

Li, L., & Wang, X. (2021). Technostress inhibitors and creators and their impacts on university teachers' work performance in higher education. *Cognition, Technology & Work*, *23*(2), 315–330. https://doi.org/10.1007/s10111-020-00625-0

Lizana, P. A., Vega-Fernadez, G., Gomez-Bruton, A., Leyton, B., & Lera, L. (2021). Impact of the COVID-19 Pandemic on Teacher Quality of Life: A Longitudinal Study from before and during the Health Crisis. *International Journal of Environmental Research and Public Health*, *18*(7), 3764. https://doi.org/10.3390/ijerph18073764

Luqman, A., Talwar, S., Masood, A., & Dhir, A. (2021). Does enterprise social media use promote employee creativity and well-being? *Journal of Business Research*, *131*, 40–54. https://doi.org/10.1016/j.jbusres.2021.03.051

Luthar, S. S., Cicchetti, D., & Becker, B. (2000). The construct of resilience: A critical evaluation and guidelines for future work. *Child development*, 71(3), 543-562. https://doi.org/10.1111/1467-8624.00164

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

Magotra, I., Sharma, J., & Sharma, S. K. (2016). Assessing personal disposition of individuals towards technology adoption. *Future Business Journal*, 2(1), 81-101. https://doi.org/10.1016/j.fbj.2016.05.003

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, *63*(2), 81–97. https://doi.org/10.1037/h0043158

Molino, M., Ingusci, E., Signore, F., Manuti, A., Giancaspro, M. L., Russo, V., Zito, M., & Cortese, C. G. (2020). Wellbeing Costs of Technology Use during Covid-19 Remote Working: An Investigation Using the Italian Translation of the Technostress Creators Scale. *Sustainability*, *12*(15), 5911. https://doi.org/10.3390/su12155911

Oksanen, A., Oksa, R., Savela, N., Mantere, E., Savolainen, I., & Kaakinen, M. (2021). COVID-19 crisis and digital stressors at work: A longitudinal study on the Finnish working population. *Computers in Human Behavior*, *122*, 106853. https://doi.org/10.1016/j.chb.2021.106853

Ortiz De Guinea, A., Titah, R., & Léger, P.-M. (2013). Measure for Measure: A two study multi-trait multi-method investigation of construct validity in IS research. *Computers in Human Behavior*, *29*(3), 833–844. https://doi.org/10.1016/j.chb.2012.12.009

Pflügner, K., Maier, C., & Weitzel, T. (2021). The direct and indirect influence of mindfulness on techno-stressors and job burnout: A quantitative study of white-collar workers. *Computers in Human Behavior*, *115*, 106566. https://doi.org/10.1016/j.chb.2020.106566

Pirkkalainen, H., Salo, M., Tarafdar, M., & Makkonen, M. (2019). Deliberate or Instinctive? Proactive and Reactive Coping for Technostress. *Journal of Management Information Systems*, *36*(4), 1179–1212. https://doi.org/10.1080/07421222.2019.1661092

Procentese, F., Gatti, F., & Ceglie, E. (2023). Protective and risk social dimensions of emergency remote teaching during COVID-19 pandemic: A multiple mediation study. *Journal of Community Psychology*, *51*(1), 67–83. https://doi.org/10.1002/jcop.22879

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The Consequences of Technostress for End Users in Organizations: Conceptual Development and Empirical Validation. *Information Systems Research*, *19*(4), 417–433. https://doi.org/10.1287/isre.1070.0165

Reynolds, R., Aromi, J., McGowan, C., & Paris, B. (2022). Digital divide, critical-, and CRISIS-INFORMATICS perspectives on K-12 emergency remote teaching during the pandemic. *Journal of the Association for Information Science and Technology*, *73*(12), 1665–1680. https://doi.org/10.1002/asi.24654

Riedl, R. (2022). On the stress potential of videoconferencing: Definition and root causes of Zoom fatigue. *Electronic Markets*, *32*(1), 153–177. https://doi.org/10.1007/s12525-021-00501-3

Rushton, C.H., Batcheller, J., Schroeder, K., Donohue, P. (2015) Burnout and resilience among nurses practicing in high-intensity settings. *American Journal of Critical Care*, 24 (5), 412–420. https://doi.org/10.4037/ajcc2015291

Sasidharan, S. (2022). Technostress in the workplace: A social network perspective. *Information Technology & People*, *35*(4), 1219–1238. https://doi.org/10.1108/ITP-09-2020-0649

Singh, P., Bala, H., Dey, B. L., & Filieri, R. (2022). Enforced remote working: The impact of digital platform-induced stress and remote working experience on technology exhaustion and subjective wellbeing. *Journal of Business Research*, *151*, 269–286. https://doi.org/10.1016/j.jbusres.2022.07.002

Suh, A., & Lee, J. (2017). Understanding teleworkers' technostress and its influence on job satisfaction. *Internet Research*, *27*(1), 140–159. https://doi.org/10.1108/IntR-06-2015-0181

Sweller, J., Van Merrienboer, J. J. G., & Paas, F. G. W. C. (1998). Cognitive Architecture and Instructional Design. *Educational Psychology Review*, *10*(3), 251–296. https://doi.org/10.1023/A:1022193728205

Tarafdar, M., Cooper, C. L., & Stich, J. (2019). The technostress trifecta - techno eustress, techno distress and design: Theoretical directions and an agenda for research. *Information Systems Journal*, *29*(1), 6–42. https://doi.org/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. https://doi.org/10.2753/MIS0742-1222240109

Tuan, L. T. (2022). Employee mindfulness and proactive coping for technostress in the COVID-19 outbreak: The roles of regulatory foci, technostress, and job insecurity. *Computers in Human Behavior*, *129*, 107148. https://doi.org/10.1016/j.chb.2021.107148

Wagnild, G. M., & Young, H. M. (1993). Development and Psychometric Evaluation of the Resilience Scale. *Journal of Nursing Measurement*, *1*(2), 165–178.

ISSN: 0718-2724. (http://jotmi.org)

Wang, H., Ding, H., & Kong, X. (2023). Understanding technostress and employee well-being in digital work: The roles of work exhaustion and workplace knowledge diversity. *International Journal of Manpower*, *44*(2), 334–353. https://doi.org/10.1108/IJM-08-2021-0480

Yener, S., Arslan, A., & Kilinç, S. (2021). The moderating roles of technological self-efficacy and time management in the technostress and employee performance relationship through burnout. *Information Technology & People*, *34*(7), 1890–1919. https://doi.org/10.1108/ITP-09-2019-0462

Appendix A: Items and references of the questionnaire

Role Ambiguity (Suh & Lee, 2017)
During the COVID-19 pandemic...
RA-01. ... I am unsure whether I have to deal with IT problems or with my work activities.
RA-02. ... I am unsure what to prioritize: dealing with IT problems or my work activities.
RA-03. ... I cannot allocate time properly for my work activities because my time is being spent on ITs-activities caries.

Computer Self-Efficacy (Delpechitre et al., 2019; Durndell et al., 2000)
SE-01. I feel confident troubleshooting computer problems.
SE-02. I feel confident to use the new technology if there is no one around to tell me what to do.
SE-03. I feel confident to use the new technology if I had just the built-in help/guide facility for assistance.

Cognitive Load (Ortiz De Guinea et al., 2013)
During the COVID-19 pandemic...
CL-01. ... I am spending more mental effort doing my work.
CL-02. ... My work is requiring a great deal of concentration.
CL-03. ... Mentally, I am having to work more to do my tasks.

Resilience (Wagnild & Young, 1993)
RS-01. When I'm in a difficult situation, I can usually find my way out of it.
RS-02. I do not dwell on things that I can't do nothing about.
RS-03. I can usually look at situation in number of ways.
RS-04. I usually take things in stride.
RS-05. I can get through difficult times because I've experienced difficulty before.

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