

Technostress Impact on Educator Productivity: Gender Differences in Jordan's Higher Education

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Abstract: This research examines the effects of technostress on educators' productivity within Jordan's higher education sector, highlighting gender differences. Technostress, characterized by techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty, adversely affects productivity. The study gathered data from 500 educators through a structured online survey, achieving a 73% response rate. Analysis revealed that technostress generally decreases productivity, with a more pronounced negative impact on male educators than females. The findings underscore the necessity for targeted interventions to mitigate technostress, particularly among male educators. Strategies recommended include training programs, policy adjustments, and organizational support to enhance the digital teaching environment. This study contributes to the understanding of technostress in Jordanian educational settings. It offers practical recommendations for enhancing e-learning practices and improving the overall educational experience and productivity in Jordan's higher education sector.

Keywords: Techno-overload, Techno-invasion, Techno-complexity, Techno-insecurity, Techno-uncertainty, Productivity, Education

1. Introduction

The widespread adoption of technology in daily life has led to increased use of information technology and the Internet, resulting in a phenomenon known as technostress. Due to this phenomenon, higher education (HE) academics face unique challenges in Jordan. The rapid shift to online and blended learning models, driven by the COVID-19 pandemic, has placed unprecedented demands on educators (Bahamondes-Rosado et al., 2023). They grapple with increased digital workloads, continuous adaptation to new technologies, and the pressure to maintain educational quality in a virtual environment (Derra et al., 2022; Fernández-Fernández et al., 2023). These challenges highlight the specific needs of HE academics in Jordan, such as enhanced digital literacy, effective stress management strategies, and institutional support to balance online and offline teaching responsibilities.

Integrating Information and Communication Technology (ICTs) into the education sector in Jordan presents unique challenges for HE academics. Beyond the shift to online and blended learning models, they need robust digital infrastructure, innovative online teaching methodologies, and more comprehensive institutional support. These needs are critical in ensuring effective online education and mitigating the negative impacts of technostress. Our study is particularly justified as there is a need for more research focusing on the Jordanian context in this domain. By exploring the specific challenges and needs of HE academics in Jordan, this study seeks to provide valuable insights into technostress and its impact on productivity within this unique setting. Such insights are crucial for developing effective strategies to enhance the digital learning environment in Jordan, ultimately benefiting educators and learners alike.

Technostress refers to the stress experienced by individuals who regularly use information systems and technological tools (Upadhyaya & Vrinda, 2021). The negative impacts of technostress can include anxiety, mental fatigue, physical ailments, technophobia, resistance, intolerance, perfectionism, terror, exhaustion, memory loss, and sleep disorders. In addition, technostress can adversely affect the business environment, leading to job dissatisfaction, decreased employee performance, reduced organizational commitment, and decreased intention to stay. Smeltzer (1987) concluded that technology-related stress can devastate organizations, including increased turnover rates, customer complaints, difficulties and problems with recruitment, and harm to the organization's internal and external image.

The COVID-19 pandemic has significantly increased the use of information systems and the Internet, with online services becoming more prevalent due to reduced face-to-face activities. However, this has also led to greater technostress and its negative consequences (Nascimento et al., 2024). Previous research has shown that

technostress is a destructive phenomenon associated with the excessive use of ICTs in various fields, including online education (Upadhyaya & Vrinda, 2021). Understanding the harmful effects of technostress in online education is crucial for educators and learners, particularly given that online education is projected to become the conventional mode of education by 2025. Although significant research has been conducted on technostress in academic circles, more studies need to focus on the specific context of Jordan. In Jordan, technological advancements and integration of ICTs (Information and Communication Technologies) into the education system have become commonplace. As a result, this study seeks to investigate how technostress adversely affects educators' productivity in Jordan and explore the potential mediating role of demographics. The primary objective is to identify the key sources of technostress and develop effective strategies for optimizing the benefits of online education by designing conducive work environments.

In contemporary society, the integration of information technology has touched almost every aspect of daily life, ranging from communication and data processing to problem-solving, marketing, and entertainment. The latest figures from the Telecommunications Regulatory Commission (TRC, 2019) in Jordan show that over 9 million people use the Internet, reflecting a remarkable 108% increase over the last five years. The development of e-technologies has witnessed the advent of e-commerce, e-mails, e-government, and, most recently, e-education (Palvia, 2013; Sethi et al., 2021). E-education has transformed the traditional approaches to teaching and learning. Online learning was introduced in the 1990s to provide remote individuals and those seeking convenience to overcome physical educational barriers. In the wake of the COVID-19 pandemic, universities and other educational institutions have increasingly relied on online learning to maintain their operations and financial performance (Palvia et al., 2018). By identifying the most influential techno stressors and developing strategies to design the workplace to maximize the advantages of online education, this study could provide valuable insights for policymakers in Jordan. These insights could help policymakers design effective interventions to minimize the negative impact of technostress on educators and maximize the advantages of online education, ultimately leading to increased productivity and satisfaction for educators and learners.

In today's world, technology has become necessary and is believed to simplify work and make it more convenient. Although the advancement of technology has the potential to improve performance and maximize profits in the education sector, it also has negative implications, such as technostress, social anxiety, social phobia, and social media addiction. Researchers have conducted valuable studies to explore the adverse perceptions and harmful impacts of technostress in various fields. Pullins et al. (2020) and Alam (2016) have investigated the negative effects of technostress on sales professionals, healthcare workers, and crew productivity in the aviation sector, respectively. While many studies focus on technostress in an organizational context, there needs to be more research on technostress among lecturers and students in the education sector (Fitzgerald, 2021). Universities must capitalize on the Internet and other technological advancements for online teaching. Volery and Lord (2000) identified the three essential success factors in online delivery methods at universities: technology, lecturer, and prior use of technology.

This study is concerned with the psychological stress educators in the education sector experience due to information and communication technology (ICT) and its impact on their productivity. Previous studies have explored the relationship between technostress and productivity, but little attention has been given to the moderating effect of demographic variables in developing countries. Therefore, this study aims to examine the influence of technostress on educators' productivity in Jordan, a developing country, and investigate the change in relationship direction and significance with the effect of gender variables. Most studies have focused on the relationship between technostress and educators' productivity in face-to-face communication. However, this study measures the relationship in the context of online/blended learning, which is prevalent due to extreme events like COVID-19 or wars that impose another lifestyle. With the sudden instruction to work from home (WFH) by many educational institutions during COVID-19, some researchers have suggested that the relationship has been reversed. Irawanto et al. (2021) found that during COVID-19, WFH reduced the stress associated with using technology in Indonesia and enhanced the quality of life.

Additionally, remote working or telecommuting is more likely to promote job satisfaction, organizational commitment, and employee productivity (Gibbs et al., 2021; Farmania et al., 2022). This study focuses on the education sector in Jordan, providing context-specific insights into the relationship between technostress, gender, and productivity. This contributes to the existing literature by considering this sector's unique characteristics and challenges. The findings can guide human resources management strategies and interventions tailored to the education sector, considering the specific needs and experiences of service providers in Jordan.

2. Literature Review

2.1 Technostress: Definitions and Features

In the 1980s, the concept of technostress was introduced by Craig Brod, a clinical psychologist who believed that technostress is a modern disease arising from the inability to cope with information systems healthily (Gaudio et al., 2017). Brod identified two distinct but related ways technostress manifests: struggling to accept computer technology and over-identification with computer technology. However, Al Masri et al. (2023)) noted that people who overly identify with computer technology may lose the ability to feel and interact with others. Champion (1988) defined technostress as the "price of using technology" and criticized Brod's view of considering it a "serious illness." He believed that technostress arises because some individuals lack the skills to cope with new technologies rather than because of the technology itself. Weil and Rosen (1997) defined technostress as any negative impact on attitudes, thoughts, behaviors, or body physiology caused directly or indirectly by technology. They found that users of technology experience technostress in both work and home settings.

According to Isiakpona & Adebayo (2011), technostress is described as a state that arises when individuals are required to adapt to new technology, especially in cases where the equipment, support, or the technology itself is insufficient. This definition and similar ones imply that technostress is synonymous with stress from technology-related factors (Agboola & Olanmi, 2016). Technostress is triggered by accelerated technologies, arrangements between these systems, and the continuous requirements from organizations, customers, and the social environment (Arnetz & Wiholm, 1997). Over the past decade, the pace of work has changed dramatically due to information communication technologies and their accompanying consequences, leading to technostress for organizations and their workers through misuse, overuse, and abuse (Gaudio et al., 2017). ICTs have introduced unwanted risks, and organizations have experienced notable adjustments in their structures and competition (McAfee, 2006).

Tarafdar et al. (2007) identified five key dimensions of technostress and techno-stressors: techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. Techno-overload relates explicitly to situations where users of information and communication technologies (ICTs) are compelled to work faster and for longer durations, handle multiple tasks simultaneously, and process substantial amounts of information within limited timeframes. This can result in physical and psychological difficulties such as tension, stress, discomfort, and memory loss (Agboola & Olanmi, 2016). Karr-Wisniewski & Lu (2010) further elaborate on techno-overload, identifying system feature overload, information overload, and communication overload as its three main dimensions.

Techno-invasion refers to the intrusive impact of ICTs that blur the distinction between work and personal domains. This phenomenon creates situations where users can be contacted and reached anytime. Consequently, individuals experience constant pressure to stay connected and be available for work-related matters, resulting in heightened stress and frustration. The continuous influx of tasks and requests contributes to the overwhelming feeling experienced by workers (Agboola & Olanmi, 2016). Techno-complexity refers to the state where the intricate nature of ICTs leaves users feeling incompetent in their proficiency. It compels them to invest time and energy into acquiring knowledge and comprehending different aspects of ICTs. According to Sweeney & Summers (2002), techno-complexity can be described as situations where employees experience a sense of inadequacy in dealing with ICTs due to their advanced and unfamiliar nature, which surpasses their existing skill set.

Techno-uncertainty pertains to situations where users face unsettled feelings due to the constant changes and advancements in ICTs. This uncertainty arises from the ongoing need to learn and educate themselves about new technologies. While individuals may initially be enthusiastic about acquiring new technological skills, continuously introducing unfamiliar and updated technologies can lead to hesitancy and frustration. Recent studies, such as those conducted by Nisafani et al. (2020) and Farmania et al. (2022), have reinforced the significance and presence of these techno-stressors.

2.2 Technostress across Different Work Settings

Exploring technostress across different work settings reveals its varying impact on job satisfaction and performance. Studies such as those by Al-Fudail & Mellor (2008), Agboola & Olanmi (2016), and Pullins et al. (2020) highlight the challenges faced by professionals in different sectors, emphasizing the need for customized strategies to manage technostress. Al-Fudail and Mellor (2008) investigated the impact of technostress on teachers and explored the drivers, consequences, and coping mechanisms associated with technostress in

teaching. They found that teachers experience technostress in the classroom due to a lack of fit between the user and the technological environment and a lack of necessary support and training. This mismatching leads to psychological consequences such as annoyance, irritation, and frustration and can negatively impact teachers' job satisfaction and performance. The authors recommend that decision-makers address environmental factors contributing to technostress and encourage teachers to adopt appropriate coping strategies such as more training, exercising, and then using and changing teaching styles. They also suggest that technostress should be incorporated into economic equations to calculate hidden costs and maximize the value of ICT investments in education. Agboola and Olanmi (2016) examined the negative impact of technostress on auditors' performance in developing countries. They suggested that boosting ICT training and stress management involvement could be protective measures to limit the impact of technostress.

Pullins et al. (2020) found that sales professionals experience high levels of technostress in their daily tasks, leading to lower job satisfaction and increased role stress. They suggest that job commitment may be a moderating variable that relates negatively to job satisfaction. Hung et al. (2015) applied the law of diminishing returns theory to their study. They concluded that while using technology may promote productivity to some extent, excessive utilization of technology can result in notable decreases in productivity among mobile phone users. Tarafdar et al. (2007) proposed a research model to investigate the impact of technostress on productivity. They found that techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty negatively impact user productivity. The effect of demographic variables on this relationship should be explored in different domains. These studies suggest that technostress is a common issue in various work settings and negatively impacts individuals' job satisfaction and performance. Proper training and support and appropriate coping strategies can help individuals deal with technostress and maximize the benefits of technological advancements in the workplace.

2.3 Technostress and Productivity within the Context of Remote Working

Remote work, especially during the COVID-19 pandemic, has heightened the prominence of technostress. Research shows that its impact on productivity varies depending on the nature, demographic variables, and digital literacy. Remote work has become increasingly popular recently, particularly due to the COVID-19 pandemic. Many businesses and universities have adapted to remote work, and the trend is expected to continue. While remote work offers numerous benefits, such as flexibility and work-life balance, it also has challenges, particularly regarding technostress and productivity. Technostress refers to the stress caused by using technology in the workplace. With the increased use of technology in remote work, technostress has become a significant issue for many workers. One study found that technostress has increased during the COVID-19 pandemic (Farmania et al., 2022). However, the relationship between technostress and productivity is complex and can be influenced by various factors.

One such factor is the nature of the job. For instance, a study by Choudhury et al. (2019) found that remote work improved productivity by 4.4% for the US patent and trademark office. However, this increase in productivity was mainly due to the simplicity of the tasks. In contrast, Kunn et al. (2021) found that remote work had a negative impact on the productivity of professional chess players, whose jobs require high cognitive demands and extensive training programs. In addition to the nature of the job, other factors that can impact the relationship between technostress and productivity include demographic variables such as age and gender and digital literacy. For instance, research has shown that males tend to experience more technostress than females, younger individuals tend to experience more technostress than older ones, and users with lower digital literacy tend to experience more technostress than those who are more proficient with digital technologies (Tarafdar et al., 2007; Tarafdar et al., 2011; Ragu-Nathan et al., 2008).

Remote work can also impact the productivity of workers with children at home. A study by Gibbs et al. (2021) found that workers with children at home are less productive than those without. However, other factors, such as increased time spent in extended meetings and reduced one-to-one communication, can also reduce productivity, as Gibbs et al. (2021) observed. Similarly, technology can lead to both technostress and productivity challenges in education. The European Commission's Digital Learning Action Plan (2018) emphasizes the importance of digital technologies in education and highlights the need for educational institutions to integrate these technologies into their frameworks. However, using digital technologies in education can also lead to technostress. Berg-Beckhoff et al. (2017) found that workers who use digital technologies in education risk experiencing technostress due to the increased workload and the need to handle large amounts of information quickly and accurately.

University lecturers and professors come from diverse backgrounds with different skill levels and competencies. Those with less ICT literacy are likelier to experience higher technostress levels and reduced productivity. The nature of their work involves instructional activities, interactions with students, and administrative tasks, each impacted by the use of technology (Tarafdar et al., 2007; Tarafdar et al., 2011; Ragu-Nathan et al., 2008). These studies highlight the complex relationship between technostress and productivity in remote work. The nature of the job, demographic variables, digital literacy, and work-life balance can all influence the relationship between technostress and productivity. Understanding these factors can help organizations and individuals manage technostress and improve productivity in remote work settings.

2.4 Technostress in Jordanian Higher Education

Technological advancements and integrating ICTs (Information and Communication Technologies) into the education system have become commonplace in Jordan. Jordan's Ministry of Education has recognized the importance of integrating technology into the education sector and has implemented several initiatives to support this goal. However, the rapid pace of technological change has also led to increased technostress among educators in Jordanian higher education. Jordanian educators face challenges including increased digital workloads, continuous adaptation to new technologies, and maintaining educational quality in a virtual environment (Derra et al., 2022; Al Masri et al., 2023; Fernández-fernández et al., 2023). These challenges highlight the specific needs of HE academics in Jordan, such as enhanced digital literacy, effective stress management strategies, and institutional support to balance online and offline teaching responsibilities. This study aims to investigate how technostress adversely affects educators' productivity in Jordan and explore the potential mediating role of demographics. By understanding educators' unique challenges in the Jordanian context, this study offers valuable insights for policymakers and educational institutions to enhance the digital learning environment. Implementing the recommended strategies can help optimize the benefits of online education, ultimately advancing the e-learning area in Jordan's higher education.

3. The Study Model and Hypotheses Development

The study refines its hypotheses to focus on the moderating role of gender in the technostress-productivity relationship. Acknowledging that men and women may experience and cope with technostress differently, it is hypothesized that gender significantly influences this relationship. According to the Job Demands-Resources (JD-R) model proposed by Bakker and Demerouti (2007), employee well-being and performance are influenced by job demands and job resources, both directly and indirectly. In this study, technostress is considered a job demand representing the challenges and negative aspects of technology use in the workplace. Technostress refers to the stress and strain individuals experience when they perceive a lack of fit between technological demands and their abilities, resources, or needs.

On the other hand, productivity, which measures employee performance, is influenced by job resources such as support systems, autonomy, and access to technology. These resources enable employees to manage technostress and maintain their productivity levels effectively. The study extends the JD-R model by examining the moderating role of gender, acknowledging that gender-specific factors can influence the relationship between technostress and productivity. It recognizes that gender may shape individuals' experiences, coping strategies, and perceptions of technostress, thus affecting how technostress impacts productivity among service providers in the education sector. By integrating the JD-R model with a gender perspective, the study provides insights into the interactive effects of technostress and gender on productivity, contributing to a more comprehensive understanding of the relationship between job demands, job resources, and employee outcomes.

Based on the theoretical framework and literature review, the study developed a model to examine the relationship between technostress and productivity in remote working and education. Established scales such as the Technostress Scale (Tarafdar et al., 2007) and the IT Stress Scale (Maier, 2014) were utilized to measure technostress. Similarly, productivity was assessed using validated scales such as the Work Productivity and Activity Impairment Questionnaire (WPAI) (Reilly et al., 1993) and the NASA Task Load Index (Hart & Staveland, 1988). Additionally, the study proposes that the relationship between technostress and productivity is moderated by gender. Technostress, characterized by techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty, imposes significant demands on educators. These demands can lead to physical and mental fatigue, decreased job satisfaction, and lower productivity. As technostress increases, educators may find it more challenging to manage their workloads efficiently, maintain high-quality performance, and achieve their professional goals. Therefore, it is hypothesized that:

H1: *Technostress negatively impacts productivity in the context of online and blended learning.*

Research has shown gender differences in the experience and perception of technostress. Women tend to experience higher levels of technostress than men, possibly due to differences in technological self-efficacy, work-life balance, or organizational factors such as role expectations and support systems. On the other hand, men may employ different coping mechanisms or exhibit different levels of resilience in dealing with technostress (Bapna et al., 2017; Huang et al., 2019). Considering these potential gender differences in technostress experiences and coping strategies, this study anticipates that gender plays a significant role in moderating the relationship between technostress and productivity among service providers in the education sector, particularly in remote working and education. Therefore, it is hypothesized that:

H2: *Gender moderates the relationship between technostress and productivity, with males experiencing a more pronounced negative impact than females.*

The study's model, depicted in Figure 1, illustrates the proposed relationships between technostress, productivity, and gender as a moderating variable.

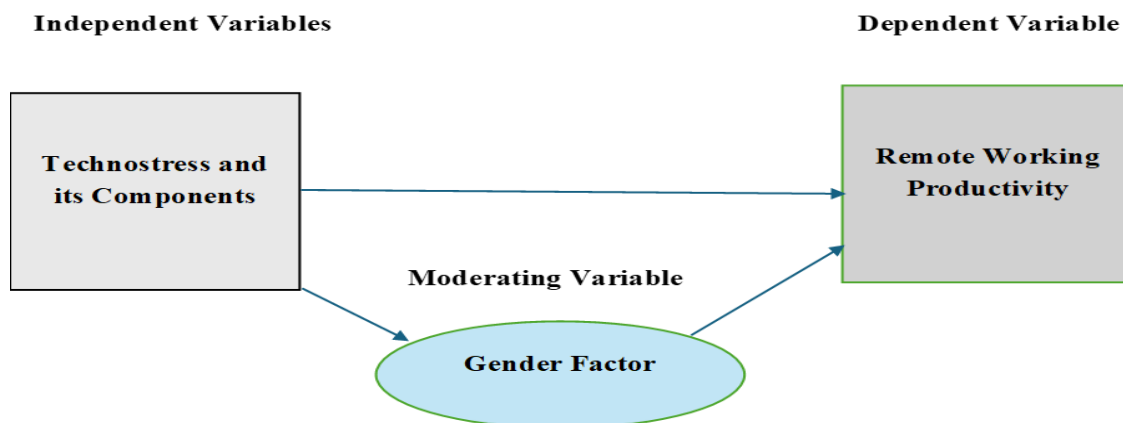


Figure 1: The study model

4. Research Methodology

This study aims to investigate technostress's impact on educators' productivity in Jordan's higher education sector, focusing on the moderating role of gender. The research design employs a quantitative approach, utilizing a structured online survey to collect participant data. Data were collected using a structured online survey distributed to educators in Jordanian higher education institutions. The survey included demographic questions, questions related to technostress, and questions assessing productivity levels. The survey achieved a 73% response rate, with 500 valid responses used for analysis. Technostress was measured using the Technostress Scale developed by Tarafdar et al. (2007). This scale includes five dimensions: techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. Each dimension was assessed using multiple items on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The reliability and validity of the scale have been established in previous studies (Tarafdar et al., 2007; Ragu-Nathan et al., 2008).

Productivity was measured using an adapted version of the Productivity Scale developed by Haynes (2007). The scale includes items that assess the perceived impact of technostress on productivity, such as the ability to complete tasks efficiently, the quality of work produced, and overall job performance. Responses were measured on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Each item was carefully selected to reflect the core idea of each dimension and modified slightly to fit the context of HE academics in Jordan, ensuring cultural relevance and clarity for the respondents. The productivity measures were similarly adapted from validated scales to align with the context of our study, providing a comprehensive assessment of the impacts of technostress.

The research process adhered to ethical considerations. Participants were provided with information regarding the study's objectives, their voluntary participation, the option to withdraw at any point, and the confidentiality of their responses. Prior to completing the questionnaire, informed consent was obtained from all participants. The personal information of the participants was carefully safeguarded to ensure confidentiality and anonymity.

The collected data were analyzed using SPSS software. Descriptive statistics were used to summarize the participants' demographic characteristics and the technostress and productivity levels. Correlation analysis was conducted to examine the relationship between technostress and productivity. Multiple regression analysis was performed to test the hypotheses and examine the moderating effect of gender on the relationship between technostress and productivity.

5. Statistical Analysis

5.1 Descriptives of the Demographic Profile

The descriptives provide a data set in terms of participant demographics and adequate experience in answering questions to support the accuracy of the responses. Table 1 includes all the descriptive data on the participant's demographics, including gender, age, working position, working experience, and academic ranking. Table 1 shows that 72% of the respondents were male, while the remaining were female.

Most of the university academics were at their most productive age, as evidenced by the fact that 49.18% of respondents in the age category were between 36 and 45. Around two-thirds of respondents (69.23%) work as faculty staff members in the academic field. 46.15% of the respondents had worked at universities where they had employment and held positions for 11 to 15 years. According to academic rankings, 38.19% of university academics are associate professors. The respondents' demographic information is summarized in Table 1.

Table 1: Sociodemographic profile (N=364)

Demographic variable	Category	Frequency	Percentage
Gender	Male	262	72%
	Female	102	28%
Age	25-35 years old	28	7.69%
	36-45 years old	179	49.18%
	46-60 years old	140	38.46%
	61 years old and above	17	4.67%
Working position	Faculty staff	252	69.23%
	Department Chairman	68	18.68%
	Dean	34	9.34%
	Vice- president	8	2.20%
	President	2	0.55%
Work experiences	Five years or less	37	10.16%
	Between 6-10 years	59	16.21%
	Between 11-15 years	168	46.15%
	Between 16-25 years	84	23.08%
	More than 26 years	16	4.4%
Academic ranking	Full professor	98	26.92%
	Associate professor	139	38.19%
	Assistant professor	96	26.37%
	Lecturer	31	8.52%

5.2 Common-Method Variance (CMV)

Using Harman's (1967) single-factor test, we assessed the CMV to see if there was a common method variance. All items were included in the factor analysis with the unrotated factor option to see if the bulk of the variance could be attributed to a single component (Podsakoff et al., 2003). The analysis's findings indicate that a single factor accounted for around 28.77% of the variance that the model could explain. Common technique variance did not represent a significant issue in our investigation because the value was less than 50%. Further evidence that the model is unaffected by common method bias was provided by the deployment of the full collinearity test when the variance inflation factor (VIF) was less than 3.3 (Kock, 2015) (see Table 2).

We used structural equation modeling (SEM), specifically PLS-SEM using the SmartPLS 3.2.8 program, to evaluate our projected hypotheses (Ringle et al., 2017). According to Cepeda-Carrion et al. (2019), PLS-SEM analyses the relationships of latent variables evaluated by indicators for explanatory purposes. When complicated models are used in the research, PLS becomes a viable choice. Additionally, PLS-SEM may be applied in various research settings and offers excellent parameter estimation efficiency, as evidenced by the method's greater statistical power when compared to CB-SEM (Hair et al., 2017). PLS-SEM allows for simultaneous examination of the measures or constructs and the underlying structural model, making it excellent for exploratory, survey-based research (Hair et al., 2012). PLS-SEM performs variance-based estimation, which is different from other models that solely consider common variance while estimating parameters.

Moreover, a variance-based approach can be employed to conduct a comparative multigroupmultigroup analysis by considering a categorical moderator variable. Specifically, the measurement invariance assessment (MICOM) technique is utilized to examine the consistency in the measurement model, followed by a multigroup analysis to identify significant differences among groups concerning estimated parameters. To evaluate our hypotheses, we adopted a two-step procedure involving assessing the measurement model and, subsequently, the structural model (Hair et al., 2019).

5.3 Measurement Model Evaluation

5.3.1 Lower order construct (LOCs) (Stage-1)

To assess the measurement model in Partial Least Squares Structural Equation Modeling (PLS-SEM), it is crucial to evaluate the reliability, convergent validity, and discriminant validity of the constructs examined in the study. The two-stage approach involves estimating the PLS-SEM path model using the PLS algorithm in stage 1, employing 5000 subsamples without any sign change. The reliability of the outer measurement model was assessed using Dijkstra-Henseler's rho (rho_A) and composite reliability (CR).). The results presented in Table 2 demonstrate that all rho_A and CR values exceeded the minimum threshold of 0.7, indicating satisfactory reliability for all measurement items utilized in the study (Dijkstra & Henseler, 2015). Convergent validity was evaluated by examining the outer loadings of the items and the average variance extracted (AVE). As depicted in Table 2, the outer loadings of all items were above 0.7, and the AVE of each construct surpassed 0.5. Hence, the findings confirmed the convergent validity of the study (Hair et al., 2019).

Establishing the distinctiveness of each lower-order and first-order construct under investigation was essential to ensuring the accuracy and validity of the findings, thereby avoiding any potential confusion. Discriminant validity was assessed to determine the extent to which a construct is empirically distinct from other constructs.

Table 2: Construct reliability and validity.

Construct	Code	Loadings	VIF	rho_A	CR	AVE
Technostress	Techno-overload					
	Information Overwhelm	0.817	1.610	0.780	0.867	0.685
	Information Response Capacity	0.816	1.561			
	Work Impact from Technology Overuse	0.850	1.570			
	Techno-invasion					
	Digital Interruptions	0.859	1.758	0.795	0.878	0.706
	Work Interference by Digital Communications	0.839	1.766			
	Compulsion to Respond	0.822	1.547			
	Techno-complexity					
	Training Need for New Technologies	0.811	1.717	0.798	0.876	0.702
	Complexity of Work Due to Technology	0.835	1.514			
	Self-assessed Technical Proficiency	0.867	1.939			
	Techno-insecurity					

Construct	Code	Loadings	VIF	ρ_{A}	CR	AVE
	Data Security Perception	0.729	1.403	0.792	0.855	0.664
	Work Impact from Security Concerns	0.843	1.623			
	Job Security Concerns Related to Tech Skills	0.867	1.559			
	Techno-uncertainty					
	Uncertainty in Using Digital Technologies	0.858	1.916	0.828	0.896	0.741
	Decision Difficulty for Digital Tools	0.875	1.920			
	Keeping Pace with New Technologies	0.849	1.783			
Productivity	Task Completion Efficiency	0.925	2.820	0.922	0.941	0.801
	Workload Management	0.870	2.715			
	Task Prioritization Ability	0.876	2.747			
	Focus and Concentration	0.906	2.456			

Fornell Larcker's criterion (Table 3) was employed to estimate cross-loadings at the indicator level, confirming that all indicators successfully loaded on their intended constructs (Hair et al., 2017). Furthermore, Henseler et al. (2015) proposed the Heterotrait-Monotrait ratio (HTMT) as a correlation measure to address cross-loading concerns. They recommended different threshold values for HTMT based on the conceptual similarity of the constructs, with a threshold of 0.85 for similar constructs. As shown in Table 4, all HTMT values were below 0.85, indicating sufficient discriminant validity for the model. In summary, the results of the PLS calculation model demonstrated satisfactory effectiveness and integrity for all constructs.

Table 3: Discriminant validity-Fornell-Larcker criterion

Construct	1	2	3	4	5	6
Productivity	0.895					
Techno-complexity	-0.483	0.838				
Techno-insecurity	-0.525	0.543	0.815			
Techno-invasion	-0.391	0.385	0.333	0.840		
Techno-overload	-0.451	0.413	0.527	0.344	0.828	
Techno-uncertainty	-0.544	0.517	0.568	0.362	0.430	0.861

Table 4: Discriminant validity-HTMT criterion

Construct	1	2	3	4	5	6
Productivity	-					
Techno-complexity	0.561	-				
Techno-insecurity	0.612	0.690	-			
Techno-invasion	0.457	0.485	0.434	-		
Techno-overload	0.531	0.525	0.687	0.435	-	
Techno-uncertainty	0.620	0.638	0.692	0.443	0.534	-

5.3.2 Higher-order components (HOCs) (Stage-2)

In stage 1 of the analysis, latent variable scores were introduced as new variables in the dataset and utilized as indicators for their corresponding higher-order components (HOCs) in stage 2. Two aspects were assessed to validate the higher-order model: (1) potential collinearity issues among the lower-order constructs and (2) the significance of the lower-order constructs. This study specified technostress as a reflective-formative higher-order construct comprising five lower-order components: techno-overload, techno-invasion, techno-

complexity, techno-insecurity, and techno-uncertainty. Potential collinearity concerns among the five lower-order components were examined to verify the higher-order hierarchical formative technostress model. The variance inflation factor (VIF), calculated as the variance ratio in a model with multiple terms to variance in a model with only one term, was employed for this purpose. A VIF value below 3.3 indicates no significant concerns regarding multicollinearity (Sarstedt et al., 2019). As depicted in Table 5, the VIF values were below the conservative threshold, indicating the absence of collinearity issues. Moreover, Table 5, Figure 2, and Figure 3 demonstrated that all indicator weights were statistically significant, affirming their relevance to the respective HOCs. Among the technostress components, techno-uncertainty exhibited the largest weight contribution (0.398, $p < 0.001$), indicating its highest level of importance. It was followed by techno-insecurity (0.283, $p < 0.05$), techno-complexity (0.218, $p < 0.05$), techno-overload (0.215, $p < 0.05$), and techno-invasion (0.208, $p < 0.05$).

Table 5: Higher-order construct validity

HOC	LOCs	Outer weights	t-value	p-value	95% Confidence interval	VIF
Technostress	Techno-overload	0.215	2.319	0.021	[0.053;0.403]	1.459
	Techno-invasion	0.208	2.461	0.014	[0.048;0.369]	1.265
	Techno-complexity	0.218	2.135	0.033	[0.016;0.413]	1.644
	Techno-insecurity	0.283	2.734	0.006	[0.083;0.495]	1.887
	Techno-uncertainty	0.398	3.989	0.000	[0.188;0.568]	1.690

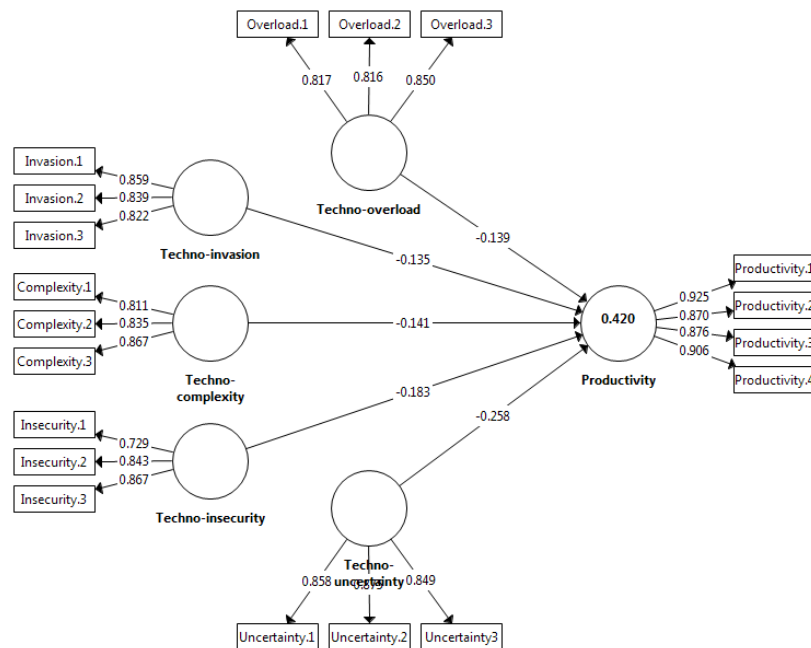


Figure 2: Measurement model (PLS) of the lower-order constructs (stage-1)

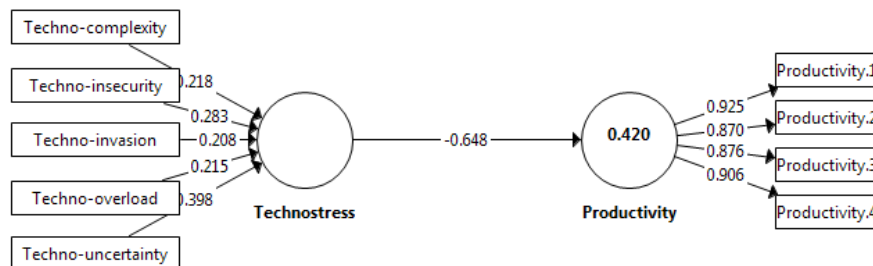


Figure 3: Measurement model (PLS) of the higher-order constructs (stage-2)

5.4 Structural Model Evaluation

After assessing the measurement model and ensuring its satisfactory performance, we evaluated the structural model. In this step, we examined various factors, including collinearity, R^2 value, SRMR value, Q^2 value, f^2 values, and significance of path coefficients. A significance level of 0.05 was used, and subsamples of 5000 were utilized as recommended by Hair et al. (2019). The collinearity test was conducted by analyzing the VIF value, and the results, as shown in Table 2, indicated that all estimations were below 3.3, indicating the absence of any multicollinearity issues in the PLS-SEM approach.

In terms of the findings, the R^2 value for productivity was determined to be 0.42, indicating that more than 42% of the variance in productivity could be explained by the significant factors identified in the study. The approach recommended by Hair et al. (2017) was utilized to assess the predictive relevance. Although the model fit measure of SRMR (Standardized Root Mean Residual) is not commonly used in PLS-SEM, the SRMR value of 0.059, which is below the threshold value of 0.08, suggests that the model fit was acceptable in this particular case, as per the guidelines of Hair et al. (2017). Based on the results presented in Table 6, Stone-Geisser's Q^2 values, calculated through cross-validated redundancy, were greater than zero, indicating that the model possessed predictive relevance, as Shmueli et al. (2019) suggested. Furthermore, the effect sizes of the outcome variables were examined using the f^2 metric, as shown in Table 6. Cohen's thresholds of 0.35, 0.15, and 0.02 were used to interpret the magnitude of effects, with values indicating large, medium, and small effects, respectively (Cohen, 1988).

The coefficients (β), confidence intervals (CI), and significance levels of the proposed hypotheses were also analyzed. The findings of the research hypotheses are presented in Table 7, revealing that technostress had a statistically significant negative impact on productivity ($\beta = -0.648$, p -value = 0.000). As a result, Hypothesis 1 was accepted based on the outcomes of the analysis.

Table 6: Model predictive capabilities

Constructs	R^2	Adj. R^2	f^2	Q^2	SUMMER
Technostress	-	-	0.725	-	-
Productivity	0.420	0.418	-	0.313	0.059

Table 7: Hypotheses testing

Structural path	Coef (β) and (T Statistics)	P-Values	Bias-corrected 95% CI		Remarks
			Lower	Upper	
H1: Technostress -> Productivity	-0.648 (17.819)	0.000	(-0.722, -0.576)		Supported

5.5 Multigroup Analysis (MGA)

In conducting the Multigroup Analysis (MGA), our sample was divided into male respondents ($n = 2762$) and female respondents ($n = 102$). While the female subgroup is smaller than the male subgroup and below the often-recommended size of 100, the robustness of our findings is supported by the successful completion of the Measurement Invariance of Composite Models (MICOM) procedure. This procedure, consisting of stages like configural invariance, compositional invariance, and ensuring equal means and variances across groups, was utilized to establish measurement invariance across the male and female groups. The results, as shown in Table 8, indicate the presence of full measurement invariance, suggesting minimal differences in the composites between the two samples and validating the feasibility of conducting MGA in this context despite the disparity in group sizes. This methodological rigor ensures that differences in path coefficients between male and female respondents are attributed to the moderating variable of gender rather than disparities in the measurement models of each group.

The results of the MICOM technique, presented in Table 8, indicate the presence of full measurement invariance. Following the guidelines provided by Henseler et al. (2016), it was observed that the study model, including the composites, items, and estimating procedure, exhibited consistency in the initial stage for both groups (male and female). The results of the MICOM procedure further indicated the completion of the second stage, as evidenced by the 95% permutation-based confidence interval (based on 500 permutations, as recommended by Hair et al., 2019), which showed that the correlation of the composites in both samples was not significantly lower than one (Table 8). This suggests minimal differences in the composites between the two samples. Since

the c values in the original data fell within the confidence interval, the null hypothesis could not be rejected. The obtained p-value was significantly more significant than 0.05, indicating that c was not significantly different from 1. Consequently, our study model is expected to exhibit compositional invariance.

Table 8: Summary of the MICOM results

Composite (Step 2)	c-value (=1)	95% confidence interval	p-value	Compositional Invariance?
Technostress	0.916	[0.812; 1.000]	0.679	Yes
Productivity	0.973	[0.995; 1.000]	0.112	Yes
Composite (Step 3a)	Difference of the composite mean value	95% confidence interval	p-value	Equal values? mean
Technostress	0.251	[-0.254; 0.253]	0.167	Yes
Productivity	-0.159	[-0.250; 0.262]	0.141	Yes
Composite (Step 3b)	Difference of the composite variance ratio	95% confidence interval	p-value	Equal variances?
Technostress	0.022	[-0.283; 0.357]	0.457	Yes
Technostress	0.019	[-0.179; 0.246]	0.173	Yes

Furthermore, Stage 3 of the research model, which examines potential differences in variances and mean values among groups in the composites, was successfully conducted. This analysis aimed to test the null hypothesis that there are no significant differences in the mean values and variances of the composites between the two groups. As presented in Table 8 (Stages 3a and 3b), the results do not provide evidence to reject the null hypothesis, indicating no significant differences in the mean values and variances of the composites between male and female respondents. The logarithm of the variance ratio and the difference in mean values of the composites, as shown in Table 8, both fell within the 95% confidence interval. This supports the conclusion of equal means and variances for the composites across the two groups/samples. These findings suggest that the measurement is robust, demonstrating the feasibility of conducting multigroup analysis (MGA) on this model's latent variables, as Hair et al. (2018) described. A multigroup analysis (MGA) was performed to compare males and females, and the results are presented in Table 9.

Table 9: Multigroup results on gender

Relationship	Path coeff. (male)	Path coeff. (female)	Diff. (male vs. female)	t-parametric	Henseler p-value
Technostress -> Productivity	-0.696	-0.472	0.224	2.654	0.008

The results indicate significant differences between the two groups regarding path coefficients. Notably, a significant difference was observed between technostress and productivity, with a p-value of 0.008 based on Henseler's criterion. These findings support hypothesis H2, suggesting that gender significantly influences the relationship between technostress and productivity.

6. Results Discussions

The findings of this empirical study, which investigated the impact of technostress on productivity while considering gender as a moderating variable, align with the Job Demands-Resources (JD-R) model proposed by Bakker & Demerouti (2007). The JD-R model suggests that job demands and resources directly and indirectly affect employee well-being and performance. In this study, the negative influence of technostress on productivity among service providers in the education sector is consistent with previous research, such as the studies conducted by Johnson & Williams (2020). The dimensions of technostress, including techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty, were found to impact productivity negatively. These findings support the idea that increased reliance on technology in the workplace

can lead to higher stress levels, which, in turn, negatively affects productivity, as Nisafani et al. (2020) suggested. By considering the moderating role of gender in the relationship between technostress and productivity, this study contributes to the existing body of knowledge in this area. The JD-R model acknowledges the importance of individual differences and factors that can influence the impact of job demands on employee outcomes. The study's findings highlight that gender-specific factors play a significant role in shaping how technostress affects productivity. This aligns with the JD-R model's emphasis on considering the role of personal resources and individual characteristics in the relationship between job demands and outcomes.

Moreover, our study contributes to the literature by highlighting the moderating role of gender in the relationship between technostress and productivity. The findings demonstrate that the impact of technostress on productivity varies between genders, with one gender experiencing a more pronounced negative impact than the other. This aligns with previous studies that have reported gender differences in the experience and effects of technostress (Bapna et al., 2017; Huang et al., 2019). For instance, research has shown that women may face unique challenges related to technology use and adaptation, which can influence their technostress levels and subsequent productivity outcomes (Bhatia & Singh, 2018). Another study by Huang et al. (2019) explored the influence of technostress on job satisfaction and work performance, considering gender differences. Their findings indicated that women experience higher levels of technostress, which subsequently affects their job satisfaction and work performance more negatively compared to men. This supports the notion that gender can moderate the relationship between technostress and productivity outcomes.

Furthermore, Bhatia and Singh (2018) investigated gender differences among information technology professionals in technostress. They found that women faced unique challenges related to technology use and adaptation, leading to higher levels of technostress. This aligns with our study's findings, suggesting that gender-specific factors should be considered when addressing technostress and its impact on productivity. Our study expands on the existing literature by providing empirical evidence of the relationship between technostress, productivity, and gender in the education sector. The findings underscore the importance of considering gender-specific factors when addressing technostress and implementing strategies to enhance productivity. Organizations and policymakers can utilize these insights to develop targeted interventions, training programs, and support systems that cater to the unique needs and challenges of service providers of different genders. By doing so, they can effectively alleviate technostress, improve productivity, and create a conducive work environment in the education sector.

By integrating the moderating role of gender, this research contributes significantly to the existing knowledge base, supporting the JD-R model's emphasis on personal resources and individual characteristics in managing job demands. Our findings reaffirm the detrimental effects of technostress on productivity and enhance understanding of how these effects are differentiated by gender.

7. Practical Implications and Limitations

The findings of this empirical study have practical implications for policymakers in the education sector in Jordan. The results highlight the negative impact of technostress on service providers' productivity, indicating the need for interventions and policies to address this issue. Firstly, policymakers should prioritize identifying and understanding technostress among service providers in the education sector. This could be achieved through comprehensive surveys or assessments that assess the prevalence and specific sources of technostress. By gaining insights into service providers' specific challenges, policymakers can develop targeted strategies to alleviate technostress and promote productivity.

Additionally, policies should focus on providing adequate training and support for service providers to cope with technostress effectively. This could include training programs that enhance digital literacy skills, provide strategies for managing technology-related challenges, and promote a healthy work-life balance in the context of remote working and education. By equipping service providers with the necessary skills and resources, policymakers can empower them to navigate technostress and enhance their productivity effectively.

Moreover, gender-specific policies and interventions are essential to address the moderating role of gender in the relationship between technostress and productivity. Recognizing that the impact of technostress varies between genders, policymakers should implement gender-sensitive approaches that consider the unique challenges and needs of male and female service providers. For male colleagues, the focus should be on enhancing technological self-efficacy and resilience training. This could involve workshops or programs designed to boost confidence in using new technologies and strategies for managing stress related to technological changes. Conversely, for female colleagues, the emphasis should be on creating supportive networks and

facilitating work-life balance. Initiatives like mentorship programs and flexible work schedules can help navigate technostress and manage work and personal life more effectively.

These interventions should be complemented by organizational policies that recognize the unique challenges each gender faces about technostress. Regular assessments of technostress levels and providing access to counseling or mental health support are key components of a comprehensive approach. Furthermore, collaboration between policymakers, educational institutions, and technology providers is crucial. Policymakers should partner with educational institutions to develop guidelines and best practices for technology integration in the education sector. These guidelines should minimize technostress among service providers and promote effective utilization of technology to enhance productivity. Technology providers can also contribute by designing user-friendly and intuitive technologies that minimize technostress and optimize productivity. Consistent with the findings of our study, Wang & Zhao (2023) underscore the need for targeted strategies to manage technostress among educators in remote working environments. This study recommends implementing mindfulness-based stress reduction programs and regular digital detox sessions, strategies supported by Weinert et al. (2020) to mitigate the impact of technostress on productivity.

Furthermore, Yang & Du (2024) highlight the importance of organizational support and flexible work policies in managing technostress. This reinforces our suggestion to develop institutional frameworks that prioritize mental health and well-being for educators. Additionally, government reports on workplace well-being, such as those by the Ministry of Higher Education, advocate for integrating mental health services and stress management programs in educational institutions. These initiatives align with our study's recommendations and provide a comprehensive approach to addressing the challenges posed by technostress.

Overall, policymakers in the education sector in Jordan should consider the findings of this study to inform the development of policies and interventions that address technostress and enhance productivity among service providers. Policymakers can create a conducive work environment that maximizes productivity and well-being in the education sector by prioritizing technostress reduction, providing training and support, implementing gender-sensitive approaches, and fostering collaboration. However, it is important to acknowledge the limitations of this study. The research was conducted in the specific context of the education sector in Jordan, and the findings need to be more generalizable to other industries or cultural contexts. Future studies could consider examining the moderating role of gender in different sectors and diverse geographic regions to enhance the external validity of the findings. Additionally, qualitative research methods could provide deeper insights into how gender influences the relationship between technostress and productivity.

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