Interplay Model of Technostress Physical Discomfort and Productivity among Teaching and Non-Teaching Employees of MSEUF: A Structural Equation Modeling Approach

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Abstract

Several studies have highlighted the impact of technostress and physical discomfort on employees' productivity. With the advent of virtual and flexible learning in the Philippines due to the Covid-19 pandemic, teaching and non-teaching employees became susceptible to physical discomfort and technostress. The study uses partial least square structural equation modeling (PLS-SEM) to examine the interplay of technostress and physical discomfort to employees' productivity at MSEUF campuses. The study's participants were the employees of MSEUF, including department heads, faculty, and non-teaching employees. The study employed quantitative research with a causal research design to measure the relationship between technostress, physical discomfort, and productivity. Using WarpPLS 8.0, the study measured the sampling adequacy using the Inverse-square root method and Gamma-exponential. Also, the measurement model and structural model were evaluated using reliability and validity tests like convergent and discriminant validity. The result shows that technostress positively affects physical discomfort with a moderate coefficient of determination (R^2) level. While technostress and physical discomfort significantly and negatively affect employees' productivity, with a moderate level of R^2. Furthermore, the result implies that during this shift in the educational systems in the Philippines, employees must be given enough support and assistance to perform at their full potential to deliver and be productive, despite the different challenges.

Keywords
Physical discomfort, PLS-SEM, Productivity, Technostress, Academic Personnel

1. Introduction
Technology has altered the world, made living easier, and is now so ingrained in people's lives that it is nearly impossible to imagine life without it. The advancement of humanity had enabled by the advent of digital technology and the growth of the Internet (Chiappetta 2017). Information and communication technology (ICT) is becoming a rapidly changing and renewing technology for higher education. Social media evolved as an essential communications tool and was discovered to be a facilitating tool for teaching and learning, particularly in higher education, as ICT tools and techniques advanced.

The Covid-19 epidemic rocked the country in early 2020, and the first day of the Enhanced Community Quarantine has changed everyone's life. Manufacturing, banks, hotels and resorts, entertainment, BPOs, and even academic institutions all came to a halt. From Basic education to colleges and Universities, everyone shifted to flexible learning and work-from-home (WFH) setup, a new condition that everyone is not ready for.

The community quarantine imposed in the whole of Luzon forced every industry and organization to fast-track its digital shift. Digitization, digitalization, and digital transformation – these buzz words became household names to us. What we have been forecasting for years happened in just one snap of a finger. Suddenly, everything became virtual and online.

Today, following the swift changes experienced in technological devices, especially in Information and Communication Technologies (ICTs), bring convenience to our lives and take us under their control. These developments give us some opportunities in business life, but on the other hand, they create some disadvantages for employees (Dragano and Lunau 2020). Nowadays, although the latest developments in business life reduce the larger burden caused by the difficulties of physical tasks, the increased speed of work and less time spent to get prepared increase the burden of psychophysical tasks (Çokla et al. 2016). The common problem experienced by employees in this condition is known as ergonomic risk or physical discomfort and technostress.

Since the outbreak of community quarantine in the Philippines, the prevalence of musculoskeletal disease (MSDs) symptoms in academic institutions has been obvious. MSDs are common complaints among workers who do static work or occupations that require repetitive upper-limb motion and extended computer usage (Poochada and Chaiklieng 2015). Office workers have reported a high prevalence of musculoskeletal disorders due to the nature of their work (Samaei et al. 2015). Due to the workstation or working configuration utilized during class or work and the fact that everything is now done online, teaching and non-teaching staff were extremely vulnerable to MSDs. Office ergonomics is one of the disciplines of ergonomics that provides a safe and comfortable working environment employing computers, laptops, chairs, and other devices.

On the other hand, technostress is described as the anxiety or negative psychological caused by the use of information and communication systems and technology. Technostress consists of five factors, namely, techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty (Chen 2015) (Zhao et al. 2020) (Salazar-Concha et al. 2021). Only a few studies have been conducted on technostress among teaching and non-teaching employees in the Philippines because most educational institutions still utilize traditional teaching or face-to-face modality. Not until the pandemic hit the world that it make everyone utilize flexible and virtual learning. This is the same as what happened in MSEUF, an educational institution catering to basic, higher education, and graduate school programs in Region IV-A. Teaching and non-teaching employees have begun to face this situation more frequently due to the WFH setup throughout all MSEUF campuses.

For more than two years now, MSEUF has implemented different work arrangements to sustain operations in all offices and levels. Some employees are full-time in the WFH setup, while others are flexible (mixed WFH and onsite). While WFH has its advantages, it also has its drawbacks. Employees who work from home miss out on social interactions with coworkers and may have fewer physical activities, such as walking between meetings. Furthermore, prolonged screen exposure from full-time computer work might result in exhaustion, lethargy, headaches, and other eye-related problems (Xiao et al. 2021).

Moreover, studies have indicated a link between physical discomfort having a positive relationship with employees suffering from technostress and having a negative impact on their productivity (Olaniyi et al. 2014) (Boonjing and Chanvarasuth 2017) (Tagurum et al. 2017) (Zhao et al. 2020).

In this study, the researchers seek to analyze the technostress and physical discomfort of teaching and non-teaching employees in the MSEUF campuses that probably affect their performance and productivity. The findings of this study should shed insight into how teaching and non-teaching employees cope with technostress and physical discomfort in the face of the COVID-19 epidemic. The study aims to raise awareness of the numerous obstacles and uncertainties that employees in the academe confront in today's world of technology and formulate an intervention program to improve employees' resiliency and well-being.

1.1 Objectives

The primary purpose of this research was to create a model for the interplay of technostress, physical discomfort, and productivity of MSEUF employees. Specifically, it describes the profile of the employees in terms of campus affiliation, work category, gender, age group, years in service, educational attainment, work arrangement, and the number of hours in WFH. It also determines the frequency level of technostress and physical discomfort experienced by employees. Similarly, it assesses the level of productivity of employees during the WFH. And finally, it develops a model that interplays technostress, physical discomfort, and productivity.

2. Methods

2.1 Research Design

The study is quantitative research utilizing a causal research design. Causal research aims to determine the size and nature of cause-and-effect interactions. Besides, it was used to analyze the effects of technostress on physical discomfort and both technostress and physical discomfort on productivity.

2.2 Research Instrument

The study is quantitative research utilizing a descriptive research design. The instrument comprises three (3) parts: the profile of employees, the technostress level assessment, the physical discomfort, and productivity. The technostress assessment questionnaires are based on Zhao et al. (2020) and Chen (2015) and are composed of five areas: techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. The physical discomfort or ergonomic risk was based on Olaniyi et al. (2014). Lastly, the productivity questionnaires were based on Asio (2021), and composed of twelve questions.

2.3 Participants of the Study

Table 1a. Demographic Profile

	Frequency	%
MSEUF Campus Affiliation		
MSEUF Main (Lucena)	112	31.9
MSEUF Candelaria	74	21.1
MSEUF San Antonio	34	9.7
MSEUF Sampaloc	30	8.5
MSEUF Catanauan	83	23.6
MSEUF Calauag	18	5.1
Work category		
Faculty/Teaching Personnel	217	61.8
Non-teaching personnel	114	32.5
Administrators/ Department Heads	20	5.7
Gender		
Male	102	29.1
Female	249	70.9
Age Group		
21–25 yo	79	22.5
26-30 yo	85	24.2
31-35 yo	45	12.8
36-40 yo	34	9.7
41-45 yo	43	12.3
46-50 yo	22	6.3
51-55 yo	16	4.6
56-60 yo	14	4.0
61 and above	13	3.7
Years in Service		
2 years or less	109	31.1
3 - 5 years	89	25.4
6 - 8 years	40	11.4
9 - 12 years	44	12.5
13 – 15 years	12	3.4
16 – 18 years	7	2.0
19 – 21 years	9	2.6
22 – 25 years	9	2.6
26-28 years	10	2.8
29 years and above	22	6.3

Table 1b. Demographic Profile

	Frequency	%
Educational attainment		
Bachelor's degree	176	50.1
Master's units	79	22.5
Master's degree	55	15.7
Doctorate units	22	6.3
Doctorate Degree	19	5.4
Work Arrangement		
Onsite work	118	38.5
Work from home (WFH)	134	33.3
Flexible (mixed WFH and onsite)	99	28.2
No. of Hours in WFH		
1-2 hrs	0	33.6
3-4 hrs	52	14.8
5-6 hrs	50	14.2
7-8 hrs	86	24.5
9-10 hrs	31	8.8
11 and more	14	4.0

Tables 1a and 1b show the demographic profile of the respondents in terms of campus affiliation, work category, gender, age group, years in service, educational attainment, work arrangement, and the number of hours in WFH. The study respondents are the teaching and non-teaching employees of MSEUF campuses. From the Basic education department, Senior high school, College academic, and non-academic departments. Furthermore, the employees who experienced work-from-home set-up and their condition during the flexible teaching and learning.

2.4 Sampling Design and Procedures

The study's sampling strategy is stratified sampling, which involves identifying the target population, determining the sample frame, selecting a sampling technique, calculating the sample size, and carrying out the sampling process.

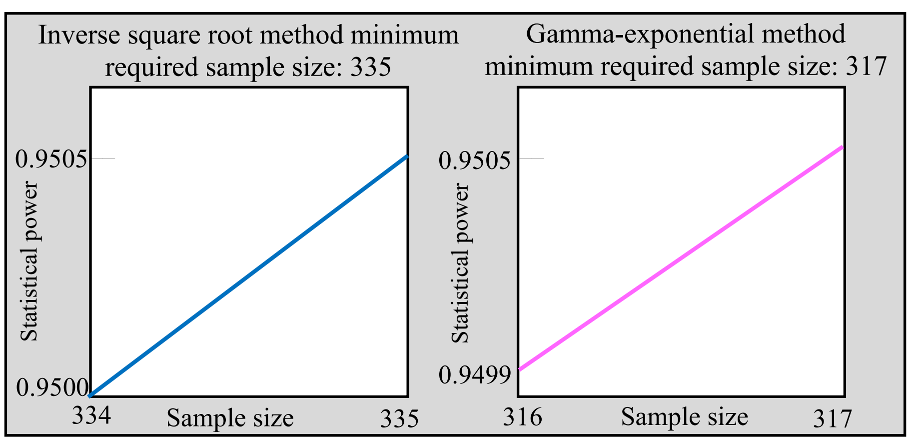

Figure 1. Results of the inverse square root and gamma-exponential methods

The survey form was sent to all the participants through Google Forms. The research used a posteriori method of determining the sample size through the WarPLS software. The researcher determined the sample size sufficiency and adequacy through PLS-SEM. Figure 1 shows the inverse square root method (335) and Gamma-exponential method

(317), with a minimum absolute significant coefficient of 0.14, a significance level of 0.05, and a power level of 0.95. With the total number of 351 respondents from the survey, the number of samples is sufficient.

3. Data Analysis Plan

The study used different statistical tools and treatments to support and answer the study's objectives; descriptive statistics and second-generation statistics - the Partial Least Square structural equation modeling (PLS-SEM). The structural model parameters were estimated using the partial least squares-structural equation modeling (PLS-SEM) method and WarpPLS 8.0 software. The measurement and structural models are assessed to evaluate the PLS-SEM results. Validity and reliability tests are included in the evaluation of the measurement model. On the other hand, the structural model is evaluated for collinearity, model path coefficients, coefficient of determination, effect magnitude, and predictive significance.

4. Results and Discussion

Relationship Between Technostress, Physical Discomfort, and Productivity

PLS-SEM was used to investigate the link between the three constructs or latent variables of technostress, physical discomfort, and productivity.

Model Fit and Quality Indices

The model fit and quality indices of the structural equation model show the summary result of the model, which includes several indices. It can be summarized using the six indices, average path coefficient (APC), average R-squared (ARS), average adjusted R-squared (AARS), average block VIF (AVIF), average full collinearity VIF (AFVIF), and goodness of fit (Kock 2019).

Table 2. Model Fit and Quality Indices of SEM

Indices	**Coefficients**
APC	0.320, P<0.001
ARS	0.440, P<0.001
AARS	0.437, P<0.001
AVIF	1.163
AFVIF	1.152
Tenenhaus GoF	0.375

Note: p-value < 0.05 - Significant / acceptable; ≤ 5 - Significant / acceptable (Hair et al. & Kock)

Table 2 displays the structural equation model's model fit coefficients and quality indicators. The results show that the SEM estimates are within an acceptable range. For the model to be acceptable, the p-values of the APC, ARS, and AARS must be equal to or less than 0.05. The recommended value for the average block VIF (AVIF) and average full collinearity VIF (AFVIF) indices is 3.3 or less. For Tenenhaus goodness of fit (GoF), an index that measures the model's explanatory capacity, the following criteria are used: small if equal to or greater than 0.1, medium if equal to or greater than 0.25, and large if equal to or greater than 0.36 (Kock 2019).

The path coefficients yield the following results: APC coefficient 0.320 with a p-value of 0.001; ARS coefficient 0.440 with a p-value of 0.001; and AARS coefficient 0.437 with a p-value of 0.001. As a result, it is significant in terms of path coefficients. Moreover, it generated coefficients of 1.163 and 1.152 in AVIF and AFVIF, respectively. When compared to the 3.3 metrics, the outcome is satisfactory. Finally, the result of the tenenhaus GoF implied a large exploratory power of the model.

Measurement Model (Outer Model)

As part of the measurement model evaluation, the validity and reliability of the constructs or latent variables are assessed. Both reflective and formative constructs were used in the model. Technostress and Physical Discomfort were in the 2nd order construct. Reliability tests evaluate the research instrument used in a study. The instrument is reliable when all participants understand the measurements or items for each latent variable. The Cronbach's alpha (CA) and composite reliability (CR) was calculated in this study. 0.70 and higher CA and CR coefficients are regarded as acceptable (Hair et al. 2011) (Hair et al. 2014) (Kock 2019).

Table 3. Model Fit and Quality Indices of SEM

Construct	**Item Loading**	**AVE**	**CR**	**CA**
Technostress				
Techno-overload	(0.713)			
Techno-invasion	(0.750)			
Techno-complexity	(0.750)	0.51	0.840	0.761
Techno-insecurity	(0.622)			
Techno-uncertainty	(0.736)			
Physical Discomfort				
1. Lower and central back pain	(0.804)			
2. Shoulder, fingers, thumb, wrist, and arm pain	(0.821)			
3. Neck pain	(0.805)	0.60	0.881	0.830
4. Headache, eye and chest pain	(0.784)			
6. Tiredness and voice impairment	(0.642)			
Productivity				
Productivity Q1	(0.858)			
Productivity Q2	(0.863)			
Productivity Q3	(0.856)			
Productivity Q4	(0.869)	0.71	0.952	0.942
Productivity Q5	(0.837)			
Productivity Q6	(0.845)			
Productivity Q7	(0.869)			
Productivity Q10	(0.746)			

Note: Item Loading - >0.5 or >0.6 – Acceptable; Average variances extracted (AVE) - >0.5 – Acceptable; Composite Reliability(CR) & Cronbach's Alpha (CA) - >0.7 – Acceptable (Fornell & Larcker, & Kock)

Based on the coefficients of CA and CR, as shown in Table 3, all the latent variables are within the acceptable range, such as technostress (CA=0.840; CR=0.761) and physical discomfort (CA=0.881; CR=0.830), and productivity (CA=0.952; CR=0.942). Furthermore, the item loading or factor loading and the AVEs generated acceptable values. A minimum of 0.622 in the techno-security and the highest is 0.869 from questions 4 and 7 in the productivity. While the AVEs range from 0.51 to 0.71.

Table 4. Square Roots of AVE Coefficients and Correlation Coefficients

	Technostress	Physical Discomfort	Productivity
Technostress	**(0.774)**		
Physical Discomfort	0.147	**(0.844)**	
Productivity	0.416	0.195	**(0.716)**

Note: Diagonal elements are the square of AVE of constructs & dimensions, while the off-diagonal elements are correlational between constructs.

Table 4 displays the correlations between variables used to establish the discriminant validity of the instrument using the square roots of AVE coefficients. The discriminant validity analyzes if the statements associated with each latent variable are clear after respondents complete the questionnaire. It also ensures that statements about one variable aren't muddled up with other variables. The square root of each variable's AVEs should be bigger than the correlations of any of the variables (Hair et al. 2014) (Kock 2019). The AVE coefficients for technostress (0.774), physical pain (0.844), and productivity (0.716).

Table 5. Heterotrait-monotrait Ratio (HTMT)

	Physical Discomfort	Productivity	Techno stress
Physical Discomfort			
Productivity	0.164		
Technostress	0.523	0.229	

Note: Good if < 0.90, Best if < 0.85)

Table 5 is the result of the Heterotrait-monotrait ratio, another measure of discriminant validity of the latent constructs. The HTMT ratios are best when their values are less than 0.85 (Henseler and Sarstedt 2013) (Amora et al. 2016) (Habtoor 2019) (Lacap 2021). Moreover, Gold et al. (2001) argued that HTMT ratios must be less than 0.90, as seen in the table, all constructs exhibit discriminant validity in terms of HTMT ratio.

Structural Model (Inner Model)

To evaluate the structural model, the researcher employed the coefficient of determination (R^2), effect size (f^2), predictive relevance of the model (Q^2), and path coefficient. The standardized coefficient in the regression analysis and the path coefficients in the PLS were similar. The f^2 represents the magnitude of each exogenous latent construct's influence on the endogenous latent construct. When an independent construct is removed from the path model, the coefficient of determination (R^2) changes, indicating if the removed latent exogenous construct significantly impacts the latent endogenous construct's value. The f^2 values were 0.35 (strong effect), 0.15 (moderate effect), and 0.02 (weak effect) (Hussain et al. 2018).

The R^2 is a measure of the structural model's prediction accuracy because it reflects the overall effect size and variation explained in the endogenous construct. The quality of the PLS route model, which is produced utilizing blindfolding techniques and cross-validated redundancy, is measured using Q^2 statistics. According to the Q^2 criterion, the conceptual model may predict endogenous latent constructs. For a certain endogenous latent construct, the Q^2 values measured in the SEM must be greater than zero (Hussain et al. 2018) Hair et al. 2011).

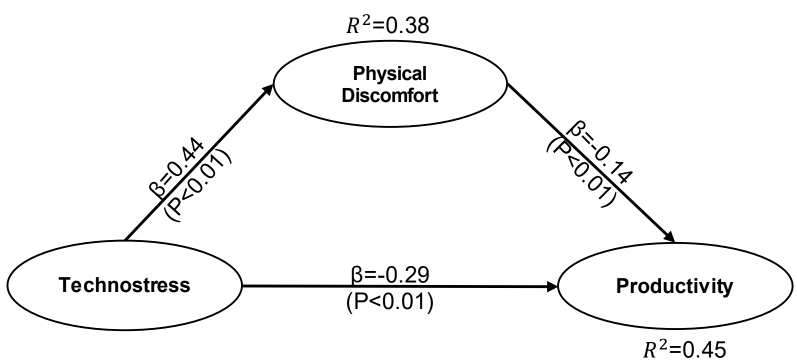

Figure. 2. Structural equation model of technostress, physical discomfort, and productivity

Figure 2 shows the structural equation model of technostress, physical discomfort, and productivity of MSEUF. The model portrays that all paths are significant with a -value of <0.01. The result depicts a positive relationship between technostress on physical discomfort. This means that as technostress increases, physical discomfort and symptoms also increase, similar to the studies of (Chiappetta 2017) (Boonjing and Chanvarasuth 2017) (Tagurum et al. 2017) (Laspinas 2015) (Tiwari 2021). In contrast, both negative relationships between technostress and physical discomfort to productivity were generated from the result. This implies an inverse relationship: as technostress and physical discomfort increase, productivity decreases, and vice versa. Several studies have resulted in work productivity and job performances being negatively impacted by technostress (La Torre et al. 2020) (Chen 2015) (Zhao et al. 2020) (Brooks and Califf 2017) (Boonjing and Chanvarasuth 2017).

Meanwhile, physical discomfort or ergonomic hazards affecting productivity and job performance are more prevalent in a more physical job like manufacturing and offices. However, teaching and non-teaching employees were exposed to this condition since the pandemic, affecting their productivity and performance. Studies have shown that physical discomfort due to the design of office workstations and the environment negatively affects their performance (Sharif and Sharif 2017) (Roelofsen 2002).

Table 6. Direct Effects of the PLS Path Model

	β	**SE**	**p-value**	**f2**
Technostress→Physical Discomfort	0.438	0.050	<0.001	0.380
Physical Discomfort→Productivity	-0.144	0.052	0.004	0.147
Technostress→Productivity	-0.286	0.052	<0.001	0.199

Note: The effect sizes (f2) were measured using the following: 0.02 = small, 0.15 = medium, 0.35 = large; SE = standard error (Cohen, 1988), β = standardized path coefficient.

Table 6 shows the direct effects of the PLS path model. The beta coefficients between technostress and physical discomfort were 0.438, implying a positive relationship. While physical discomfort to productivity and technostress and productivity were -0.144 and -0.286, respectively. The negative beta coefficient indicates an inverse relationship between the construct, which means that when the exogenous variable increases, the endogenous variable decreases, or vice versa. Also, the standard error of the three constructs was 0.050, 0.052, and 0.052, respectively.

Moreover, the largest effect size was recorded at f^2=0.380, between technostress and physical discomfort; thus, it implies that technostress has a large effect on physical discomfort. While the second was f^2=0.199 from technostress and productivity, indicating medium effects. Lastly, physical discomfort and productivity have a medium effect with a coefficient of 0.147.

Table 7. Predictive Relevance, Collinearity, and Coefficient of Determination

Construct	**Full collinearity VIF**	**R^2**	**Q^2**
Technostress	1.237		
Physical Discomfort	1.216	0.380	0.192
Productivity	1.045	0.452	0.106

Note: For R2: 0.19-weak, 0.33-moderate, 0.67-substantial. For Q2: The values measured must be greater than zero to recommend that the conceptual model can predict the endogenous latent constructs. For FCVIF: <5 is acceptable (Hair et al. & Kock).

The full collinearity VIF, predictive relevance (Q^2), and coefficient of determination are shown in Table 7. The full collinearity variance inflation factor of the path model of the latent variables, technostress (1.237), physical discomfort (1.216), and productivity (1.045), all are within the acceptable range. The R^2 coefficients of 0.380 for physical discomfort and 0.452 for productivity reflect the predictive accuracy of the exogenous variable on endogenous variable/s. Therefore, the R^2 generated from the model was moderate.

Finally, predictive relevance was also evaluated using the Stone-Geisser test or simply Q^2. To say that the measurement model has predictive validity, the values of Q^2 should be higher than 0 (Kock 2019). The predictive relevance for physical discomfort is 0.192, and productivity is 0.106. Hence, the Q^2 values are all greater than 0, which means that the model has the ability to predict.

Framework of Technostress, Physical Discomfort, and Productivity

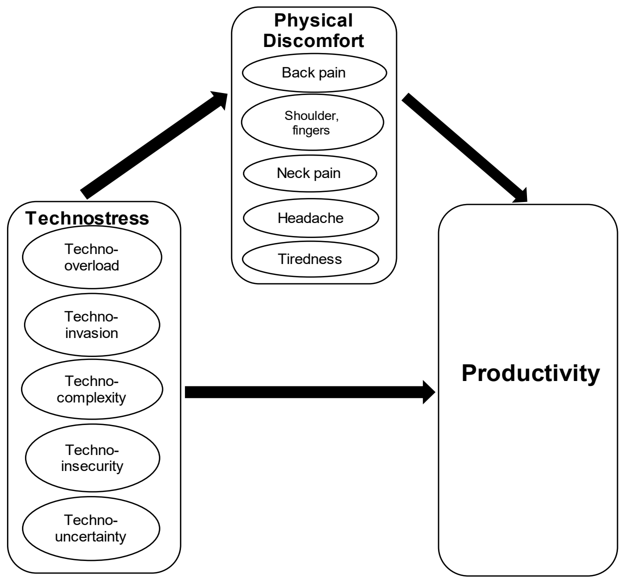

Figure 3. Framework of Technostress, Physical Discomfort, and Productivity

Figure 3 shows the framework of the three constructs, technostress, physical discomfort, and productivity. The framework was supported by the result of the structural equation model using WARP-PLS, showing the connections of each construct and dimension. Technostress, in general, is significant to the physical discomfort and productivity of teaching and non-teaching employees, which is composed of 5 stressors, techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. Likewise, physical discomfort is significant to employees' productivity. Physical discomfort manifests in back pain, shoulder, fingers, thumb, wrist, and arm pain, Neck pain, Headache, eye and chest pain, tiredness, and voice impairment.

6. Conclusion

In general, the majority of the respondents were teaching personnel from the Main campus; most of them belonged to generations Y (millennials) and Z (iGen), with eight years or less tenure at the University. The respondents are mostly WFH and flexible working arrangements, and the majority are working about 8 hours and below every day. Among the five techno stressors, techno-overload is primarily the concern of the employees. While on the other hand, the majority of the workers experienced lower and central back pain during the WFH. The path analysis revealed a significant relationship among the three constructs, and technostress positively correlates with physical discomfort. In contrast, technostress and physical discomfort have a negative impact on the work productivity of MSEUF employees.

The study will prove useful to institutions as they decide how to design nuanced strategies that address technostress and its impact on employees. The findings suggest that reducing technostress effectively reduces physical discomfort, thus improving productivity and job performance in general. However, studies also show that technostress has a good impact; therefore, institutions should aim to understand what each specific type of technostress is ideal for employees to perform well. The results suggest that institutions benefit from using tools such as MS Teams and Zoom Meeting to encourage employee innovation when it comes to techno-overload. Institutions can use education and training to help employees approach techno-overload as a challenge rather than an interference to function positively rather than negatively.

The researchers also found that techno-invasion can lead to a positive impact under the right set of conditions. Employees may see technology stealing from their personal life detached from the workplace. However, techno-invasion can be advantageous for employees with the right precautions. In order to break techno-invasion-causing technostress, employees should know their boundaries and learn when to be disconnected. When it comes to techno-complexity, the researchers recommend that institutions provide opportunities for mentoring. The transfer of knowledge should happen in both directions. The senior employees will be the mentors and the junior employees who have advanced knowledge of new technologies.

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Biography

Dr. James Louie Meneses is an experienced professor, consultant, Industrial engineer, and researcher. As a professor, he teaches industrial engineering courses, including research, operations management, operations research, feasibility studies, and ergonomics. As a consultant, he works in industrial engineering designs, management, quality management systems, and data analysis. In his early professional life, he worked as a Quality control engineer and Management trainee in a Manufacturing company. Currently, he is working as a full-time professor and a research coordinator at Manuel S. Enverga University Foundation, Philippines. His role as a consultant is mainly related to the quality management system, quality and system improvement. He works closely with researchers in data analysis, applying 1st- and 2nd-generation statistics (Structural Equation Modeling). His work as a researcher is mainly associated with using the lean six-sigma methodology, ergonomics design, and Partial Least Square Structural Equation Modeling (PLS-SEM). He holds a Doctor of Philosophy in Management at Lyceum of the Philippines Laguna and earned his Master in Engineering majoring in Industrial Engineering at Adamson University. He presented his work in several research fora, where he has been awarded best presenter and research paper.