

The Effect of Age on Generative AI Usage, and the Mediating Role of Technological Stress

Josua O. Sprengers

Tilburg University

761990-B-12 - Bachelor's thesis HRS-People management

Dr. Christine Yin Man Fong

June 1st, 2025



Abstract

As generative AI (GAI) becomes more prevalent in the workplace, understanding who uses the technology has become increasingly important to both academia and organisations alike. Based on the Job-Demands-Resources theory, this study investigates whether an individual's age predicts their self-reported GAI usage, and whether technostress mediates that relationship. A cross-sectional survey was administered to 185 professionals. Age, GAI usage, and technostress were measured with validated Likert scaled and analysed in SPSS.

Contrary to expectations, age showed no significant association with either GAI usage or technostress. The indirect effect through technostress was also non-significant. Technostress did show a significant positive association with GAI usage, suggesting that employees may turn to GAI even when dealing with stressors caused by technology, rather than withdraw from it. These findings challenge common stereotypes that older people tend to struggle more with technology and highlight the surprising role of technostress in increasing GAI usage. Theoretically, this thesis underlines how the JDR can be applied to the context of GAI, while it practically highlights the relevance of understanding which factors influence GAI usage, and which factors should or should not be considered when integrating GAI tools into the workplace.

The Effect of Age on Generative AI Usage, and the Mediating Role of Technological Stress

With generative artificial intelligence (GAI) tools quickly becoming integrated into the modern workplace, creating a comprehensive understanding of how individuals of different age groups experience and adapt to these technologies has become increasingly relevant both for organisations and academia alike. GAI, as defined by Feuerriegel et al. (2024), refers to the computational technology that has enabled users to generate evidently new and relevant context such as images, videos, text, and more, from the data the technology is trained on. Both corporate organisations and academia have expressed their concerns with adapting to new technologies like GAI, and the psychological strain that could come with it (Felemban et al., 2024; Popescu et al., 2024; Wang & Yao, 2025).

Along with the emergence of GAI, there have been drastic changes to the way many fields operate, thus sparking discussions about the potential impacts of GAI usage on society in all aspects (Miyazaki et al., 2024).

GAI has emerged as a rapidly growing subset of AI, with interconnected and integrated relevance across the ICT landscape, experiencing substantial growth in terms of global adoption and usage over recent years (Ali et al., 2025) Research done by Rahman et al. (2024) concerning GAI usage, found that older participants showed more apprehension and resistance in terms of AI acceptance than younger participants. A study by Nimrod (2017), suggests that the continuously needed adaptation to new technology demands a significant psychological price. The study also further indicated that this technological stress should be considered a threat to wellbeing in one's life, highlighting the importance of considering technostress in research.

When it comes to defining *technostress*, the term has quite a substantive history and ever-changing definitions. The earliest definition of the term comes from Brod (1984, p. 16), who

defines technostress as a modern disease of adaptation which is a result on the inability to cope with emerging technologies in a healthy way. Ragu-Nathan et al. (2008), define technostress (TS) as an IT user's experience of stress when engaging with technologies. This paper will use a more modern definition of technostress, as defined by Urukovičová et al. (2017), who define it as a multidimensional concept concerning psychological stressors, where the problem is both technology anxiety as well as the burden caused by information overload. This modern definition was chosen due to its inclusion of both technology anxiety and information overload concerning stress, which fit the theme of GAI usage within this paper.

A study by La Torre et al. (2019), highlights the relevance of TS by its consequences, such as a decrease in job satisfaction, performance, and increases in work-overload and work-life balance conflicts, none of which can be considered positive. The study further emphasizes the many effects TS can have on the workplace and the great variety of consequences it will have for organisational outcomes. Similarly, a study by Tagurum et al. (2017), showed that technostress significantly impacted job performance, highlighting the frustrations and struggles that came with the use of technology as the antecedents of their decreased productivity. These findings are in line with those of Atrian and Ghobbeh (2023), who found that technostress adversely affected job performance, productivity, and satisfaction, as well as increasing turnover intentions.

The literature on the relationship between age and GAI usage is very limited, especially when considering the possible role of technostress, a gap that this thesis will address .

To properly explain the underlying mechanisms of the relationship between age and GAI usage, and the role of technostress, this thesis uses the Job-Demands Resource Model (JDR-Model) as a theoretical foundation. This model states that the demanding factors of one's job are those that require prolonged mental or physical effort, such as high work pressures and excessive

workloads, which can lead to stress, exhaustion and long-term burnout (Demerouti et al., 2001; Schaufeli & Bakker, 2004). It is particularly useful in the context of rapidly evolving technologies like GAI, where the benefits the technology provides and the demands that come with it are two sides of the same coin. Similarly, a study by Pansini et al. (2023) suggests that continuously using Information Communication Technology (ICT) at work may exhaust employee resources, increasing the risk of stress and burnout. In terms of technostress, a study by Wang et al. (2021), found that technostress creators are significantly associated with burnout, which negatively affects other aspects of life. These findings suggest that technostress has significant effects on wellbeing and is an important fact to consider when implementing the usage of ICT and GAI tools. These findings indicate that technostress is not just a mild workplace trouble but, in the current climate, presents a vital factor that affects employee health and wellbeing. This is especially the case among older individuals, as research suggest that they are at higher risk of stress and burnout (Alhaffar et al., 2019)

Properly understanding generational differences in AI usage and their experience of technostress is essential in developing effective training programs and implementing policies that enable the usage of ICT and GAI tools within the workplace. While previous literature has tended to focus on general attitudes or skill, a research paper by Yi et al. (2013) found that age, among other individual attributes, can significantly influence how new technologies are perceived and used. The framework presented in this paper highlights that age influences technology usage through its perceived usefulness and ease of use. Its findings highlight that age remains to be a relevant and underexplored factor in the adoption and integration of emerging technologies like GAI. However, when it comes to specifically GAI usage between different generations, the literature is quite limited. Although age is often treated as a demographic control

variable, its potential influence on dimensions of GAI use, such as digital confidence or coping with complexity, may be more meaningful than the current literature acknowledges it to be, as it is most often only considered as a control variable.

As such, this research paper will further extend the relatively limited literature on the effects of age on generative AI usage, with a particular focus of the effects of technostress as a mediator within that relationship. By applying the Job-Demands Resource Model, it will analyse this relationship and contribute to our current understandings of GAI usage. Through the JDR Model, it will elaborate on the dual role of GAI, and how GAI usage differs in each respective role. The dual role refers to the possibility that GAI may function as either a job demand, leading to strain, or as a resource, enhancing autonomy and efficiency (Pansini et al., 2023; Tarafdar et al., 2015). These studies discussed this dual role, showing that an employee's perception of technology as either a hindrance or an enabler highly depends on their perceived available resources, such as digital skills or perceived organisational support. Furthermore, the studies showed that employees might disengage from using GAI when experiencing stressors, which highlights the importance of investigating the relationships between these constructs

This thesis will further explore the nuances in these relationships, and how they may differ across those of different age groups. To properly explore these relationships and to answer the research question, the following part of the paper will define the main constructs, as well as provide a thorough explanation of the theoretical paradigms used in the argumentation of the paper. Each section will provide needed information, peruse theoretical perspectives, and examine evidence to form a hypothesis. These hypotheses will be summarized in a conceptual model at the end of the section. In terms of implications, theoretically this thesis will substantiate the limited literature on GAI usage, which is especially limited in relation to age and

technostress. Practically, this thesis hopes to shed light on the effect that age has on GAI usage and be of interest to those who form policies regarding the integration of GAI into the workforce.

Theoretical Framework

Age and Generative AI Usage

The following section will define generative artificial intelligence (GAI) usage, after which the relation between age and GAI will be analysed using the job demands resource model (Demerouti et al., 2001), resulting in the formulation of the first hypothesis.

The term "generative AI usage" describes the scope, duration, and regularity with which someone uses a generative AI tool (Gashemagaei, 2020). In recent years, GAI has caused a revolution in both business and society as a whole, altering the ways that businesses operate, as well as changing the dynamics of how they fit within society (Bharadiya et al. 2023). GAI usage has seen a sharp uptake in usage over recent years, and has now become widespread, being used by professionals across many different fields and sectors (Bright et al., 2024). Working professionals have been positive about its use, but also exercise caution, as some fear it might lead to negative outcomes such as job loss, and an increased workload, instead of positive ones (Bright et al., 2024; Schlögl, 2019). GAI has created both opportunities and challenges within numerous fields, influencing business, technology, education, healthcare, and more (Nah et al., 2023). However, Nah et al. (2023), also highlight that GAI usage can bring many challenges to society, ranging from misuse and overreliance to authenticity and adaptability issues. GAI could lead to large scale manipulation of digital media, aggravating the issue of false information being spread (Graganiello et al., 2022). These challenges are highlighted by Afzal et al. (2023), as it was found that the digital divide between younger and older generations presented a significant challenge in terms of digital literacy. Digital literacy is defined as an individual's possession of

the required skills and abilities to perform tasks and solve issues within digital environments (Reddy et al., 2020). Younger generations were found to have higher levels of access in comparison to older generations, thus increasing the ease of acquiring information in comparison to their elders. Older generations were also more likely to experience frustrations when using technology, and difficulties in understanding the workings of GAI, and more so expressed their resistance to the seemingly unbound use of the technology (Chan & Lee, 2023; Georgescu et al., 2024)

Conversely, older generations have shown interest in learning new technological skills, but appreciate more self-paced and flexible learning methods, whereas younger generations seem to prefer a fast-paced crash-course style learning method, indicating different engagement and usage patterns when it comes to technology among different age groups (Foster et al, 2016; Pang et al., 2021; Urick, 2017). Consequently, while it seems that older generations are trying to keep up with the younger generations, they need to overcome the seemingly time-consuming barrier of training first. Similarly, a study by Çoklar and Tatli (2021), found that digital nativity, the usage of, and being comfortable with technology, is significantly more present in younger generations than in older ones. The integration of technology has proven to be challenging for older generations (Nakagawa & Yellowlees, 2020). Lastly, a study by McFarland (2001) reported that age has a significant direct association with the usage of technology.

These findings are in line with empirical findings of the Job-Demands Resource (JDR) theory. The aforementioned theory states that there are two categories of working conditions: Demands, which are elements that are related to exhaustion and burnout, and Resources, which are elements that are negatively related to work disengagement (Demerouti et al., 2001). High job demands lead to strain, which lead to worsened organisational outcomes. However, high

resources do the opposite, and motivate employees by intrinsically and extrinsically supporting them, leading to improved organisational outcomes (Kim & Christensen, 2017). A study by Ning and Alikaj (2018) found that older workers were more frequently found to view interacting with technology as a demand, rather than a resource, due to them viewing technology as draining and disruptive to their routines and procedures. Based on these findings, in line with the principals of the JDR, those that are higher in age seem to be more likely to struggle with and be opposed to the usage of technology such as GAI tools.

The above findings indicate that the adoption of GAI is not evenly distributed across age groups. Older generations are often met with greater barriers to using GAI, such as lower digital literacy, discomfort with technology and viewing GAI as a demand rather than a resource. On the other hand, younger generations seem to be more digitally literate and adaptable, seeing GAI as a useful tool and a more manageable challenge. The JDR supports this sentiment, as fundamentally the theorem states that job resources buffer the effect of job demands. As such, those that are less efficient with their resources will experience the effects of the demands more. In this case, those of with a higher age seem to struggle more with their digital literacy, and consequently view GAI as a demand, hindering the likelihood of engaging with it, leading us to the formulation of the first hypothesis of the present study:

H1. There is a negative association between Age and self-reported Generative AI usage

Age and Technostress

This section will define Technostress and elaborate on its relationship with age, and what influence age has on technostress. Furthermore, it will go over the JDR perspective on said relationship, ultimately leading to the formulation of the second hypothesis.

Technostress (TS) can be defined as a complex psychological concept referring to stressors causing issues with regards to technology anxiety and information overload (Urukovičová et al., 2017). As previously mentioned, TS has an extensive history, but just as technology evolves and becomes more integrated into daily life, the definition of TS must be inclusive of the modern implications of the word. As found by Nimrod (2018), older adults experience TS differently compared to middle-aged or younger users of technology. Younger generations, who grew up with digital technologies starkly contrast older adults, who are considered digital immigrants and more often feel left behind and overwhelmed by the evolution of technology (Çoklar and Tatli, 2021; Nimrod, 2018). This exemplifies the concept of the somewhat ambiguous ‘digital divide’, a distinction of those who do and those who do not have access to, and an understanding of ICTs (Van Dijk, 2012). As such, these differences between generations show that older generations might experience more stress than younger ones.

Furthermore, older generations experience more difficulty with technostress creators such as techno-complexity, which refers to how complex technological systems are, and techno-insecurity, how insecure one’s job feels as a result of technology threatening their job security (Tarafdar et al., 2015). These factors lower their familiarity with digital environments (Tarafdar et al., 2015). This lower digital literacy heightens technostress and is more often found among older generations (Setyadi et al., 2017) A study by Marchiori et al. (2019) echoes this thought, finding that older generations tend to perceive the technological environment of the organisation as more complex than younger generations. However, research on the effect of age on technostress shows some variability between studies, depending on the research context and population (Mahapatra & Pillai, 2018; Marchiori et al., 2019). Nevertheless, these studies show that there is a consistent pattern suggesting that age positively influences technostress.

As seen by the JDR model, personal resources influence dealing with demands, and as shown by Ning and Alikaj (2018), different age groups require and use resources differently. The JDR emphasizes personal resources like autonomy and competency as being key psychological drivers that affect demands and stressors. Furthermore, Ning and Alikaj (2018) explain that older generations often perceive new technologies as disruptive to routines, rather than helpful, which is in line with the JDR's concept of hindrance demands. These hindrance demands are work-related demands that tend to limit an individual within the workplace and hinder their ability to perform (Gomoll, 2018). Technostress acts as a hindrance demand that exhausts personal resources such as autonomy and social support (Pansini et al., 2023). These are resources that may already be perceived as limited by older generations, thus increasing the perceived demands on this age group (Ning & Alikaj, 2018).

Building on this understanding from previous literature and the framework provided by the JDR model, the second hypothesis was proposed:

H2. Age is positively associated with technostress

Technostress and Generative AI Usage

This section will discuss the effect of the mediator Technostress (TS) on Generative AI (GAI) usage by applying the Job Demands-Resources (JDR) model, leading to the formulation of the third hypothesis.

In line with the JDR model, technostress can be seen as a hindrance demand, one that reduces personal resources and hinders individual performance, because stress can hinder one's ability to perform (Leblanc, 2009; Pansini et al., 2023). This study also shows that technostress decreases technology adoption and increases avoidance behaviours, due to users feeling overwhelmed. Furthermore, it was found that technostress often exhausted employees' resources,

such as autonomy, social support and time, increasing the risk of stress, burnout and disengagement. Similarly, Tarafdar et al. (2015) found that technostress creators, such as techno-complexity, -insecurity, and -overload, have been linked to higher job stress, and decreased job satisfaction and productivity. When experiencing these stressors, individuals often respond with withdrawal behaviour as a coping mechanism, which undermines the benefits of the usage of technology (Tarafdar et al. 2015).

This behavioural pattern can also be seen in the context of GAI usage. Research by Zhang and Tong (2024) shows that AI-specific technostress, which is driven by fear of misuse, complexity, and uncertainty, reduces adoption intentions and increases disengagement. Those who view GAI as overly complex and unmanageable are more likely to simply avoid using it completely. As such, the third hypothesis was proposed as follows:

H3. Technostress is negatively associated with Generative AI usage

The Mediating Role of Technostress

This last section of the theoretical framework will discuss the mediating role of technostress on the relationship between age and GAI usage. This will lead to the formation of the fourth and final hypothesis.

As established in the first section of this framework, age can play an important role in establishing how individuals use GAI. Older generations often face barriers such as lower digital literacy and resistance to technological change when exposed to new technologies (Chan & Lee, 2023; Nimrod, 2018). In line with the JDR, these factors contribute to the perception of GAI as a demanding and unfamiliar technology, which could demonstrate the lower adoption rates found among older generations (Çoklar & Tatli, 2021; Ning & Alikaj, 2018). Therefore, older generation seem less likely to use GAI more often than their younger counterparts.

Building on this, the second section illustrates that older generations tend to be more likely to experience technostress, mostly due to their perception of GAI usage as a high demand in combination with limited personal resources such as autonomy or support. Studies have shown that older generations are more likely to perceive technologies, including GAI technologies, as overwhelming and depleting to personal resources, leading to increased levels of strain and stress (Chang et al., 2024; Pansini et al., 2023; Tarafdar et al., 2015). Consequently, it seems that those older generation experience more stress.

The third section investigated the impact of technostress on GAI usage directly. Technostress had been shown to act as a barrier to the adoption of GAI tools, especially due to users feeling overwhelmed or uncertain about them, leading to them avoiding usage or failing to use GAI effectively (Chang et al., 2024; Zhang & Tong, 2024).

In conjunction, these findings suggest that technostress might serve as a mediator in the relationship between age and GAI usage. From the perspective of the JDR, older generations may experience higher demands and lower resources when faced with GAI technology, contributing to increased technostress and subsequently lowering the usage of GAI tools. This has led us to the final and fourth hypothesis:

H4. The negative relationship between age and generative AI usage is mediated by technostress.

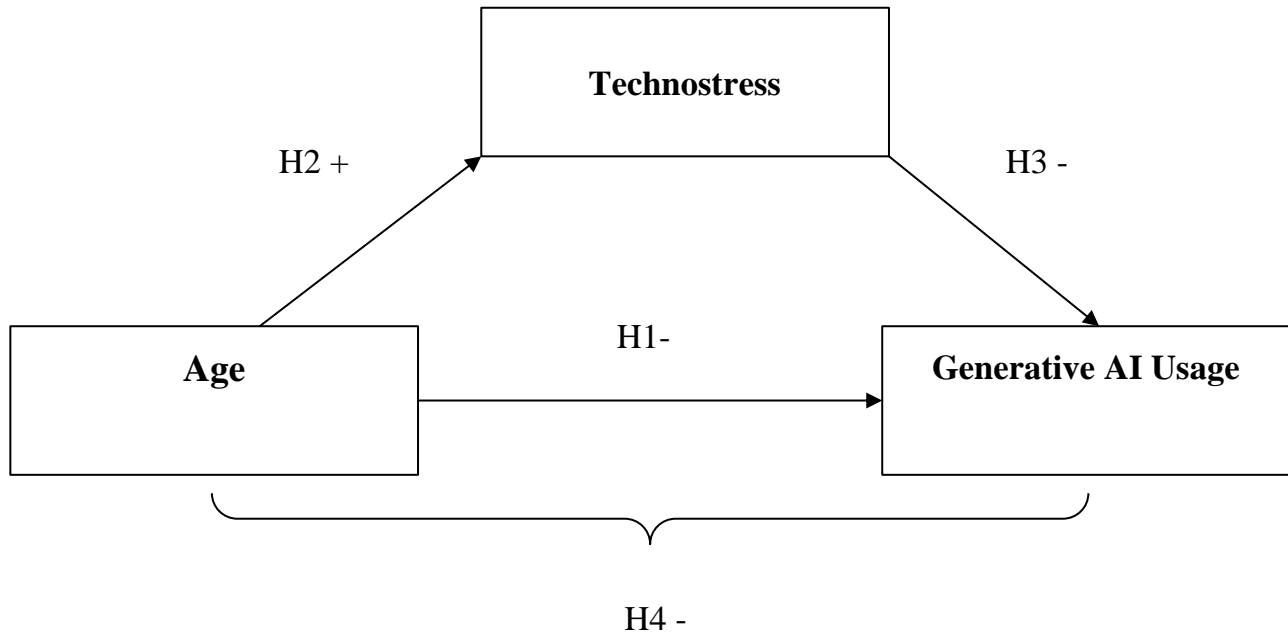


Figure one. Conceptual framework including hypotheses (H1 - H4)

Methods

This research paper was focused on the relationship between age and generative artificial intelligence usage, with technostress as a mediating variable. To appropriately investigate the hypotheses shown within the conceptual model, existing quantitative data was used in conducting this cross-sectional study. Data was collected through a questionnaire. The hypotheses within this paper were analysed on the individual level. All variables, including age, GAI usage and technostress were all measured through self-reports on the questionnaire, which is on the individual level.

Sample

The questionnaire was completed by 185 employees. Participants were part of several different industries, ranging from agriculture and utilities to finance and data processing. This data was collected through a data collection platform. Participants were employees who filled out

an online questionnaire via Qualtrics. The average age of the employees within the same was 36.19 ($SD = 10.25$). The majority of the sample was male (64.86%). Participants worked an average of 38.31 hours per week ($SD = 6.26$).

Procedure

A dataset recruited by my thesis supervisor was used, which was collected via a data collection platform. Participants were employees who filled out an online questionnaire via Qualtrics.

Instruments

As for the variables researched within this paper, all were measured with established and validated scales.

Generative AI usage was measured at the individual level. This construct was measured through a 13-item scale by C. Fong in an unpublished manuscript (2025). The items were measured using a 5-point Likert scale, with values ranging from ‘‘Never’’ (1) to ‘‘Always’’ (5). An example from this item scale is: ‘‘At work, I proactively use generative AI to automate repetitive tasks’’.

Similarly, Technostress was measured at the individual level. This construct was measured through a 5-item scale introduced by Urukovičová et al. (2023). The items were measured using a 5-point Likert scale, with values ranging from ‘‘Strongly disagree’’ (1) to ‘‘Strongly agree’’ (5). An example from this item scale is: ‘‘I often find it too complex for me to understand and use new technologies’’.

In order to check whether the data was appropriate for exploratory factor analysis, the Kaiser-Meyer-Olkin (KMO) test of sampling adequacy and Bartlett’s test of Sphericity were

conducted (Barlett, 1954; Kaiser, 1974). The Test of Sphericity must be significant for the data to be appropriate, while the KMO index must be over 0.6 (Barlett, 1954; Kaiser, 1974).

Furthermore, to test the reliability of the scales, Cronbach's Alpha was calculated for each construct. For this thesis, an alpha of 0.8 was considered good. In order to determine the number of extracted factors in the data, eigenvalues were calculated, and in accordance with Kaiser's rule, those that had an eigenvalue above one, were extracted (Kaiser, 1974).

Subsequently, a Principal Axis Factoring (PAF) was performed in order to explore the underlying factor structure and identify the possible latent constructs within the data.

Lastly, control variables were not included in this study. This decision was made considering both theoretical relevance and statistical clarity. As the independent variable, age is a stable and inflexible demographic factor, that inherently is not influenced by factors such as gender industry or hours worked. A study by Li (2021) found that adding other control variables risks including unnecessary overcontrol bias. This could erase meaningful variance that explains the theoretical relevance of age in this context. Similarly, Berneth and Aguinis (2016) emphasize the relevance of only including control variables when they are theoretically justified and empirically shown to be confounding factors.

Subsequently, when it comes to this thesis, in understanding how age influences GAI usage and the mediating role of technostress, controlling for other variables could misrepresent relationships of interest, rather than offer clarity. As such, no control variables were used in this study to ensure that it remains focused and aligned with the main research question.

Analysis

To properly investigate the research question as to whether technostress mediates the relationship between age and generative AI usage, through the compilation of theory, a

conceptual model was created, which offered four hypotheses. The data analysis for this thesis was conducted using IBM SPSS version 28. Before data analysis, the data was screened and cleaned for errors. During data analysis, descriptive statistics, correlations, reliability tests, and component analyses were performed. Subsequently, all of the hypotheses were tested using the PROCESS extension (version 4.2) in IBM SPSS 28 (Hayes, 2017). Furthermore, the mediation relationship was tested using Model 4 within the PROCESS extension. This was done as it reduces user-error in calculating mediation effects, a risk that must be taken into consideration due to the nature of the mediation model (Hayes, 2017).

To properly assess the mediating effect in this research, the analysis was carried out using the PROCESS extension, which is in line with the recommendation by Hayes (2017). To further reduce the risk of sampling error concerning the indirect effects, the number of bootstrap samples was set to 5000 (Hayes, 2017). Bootstrapping refers to the process of repeatedly resampling the observed data to generate a sampling distribution, while keeping the original sample size constant (Hayes, 2017). To test the hypothesised mediation model in this thesis, PROCESS Model 4 was selected, which was made to assess simple mediation (Hayes, 2017). A 95% confidence interval was applied to assess the significance of the indirect effect. If the aforementioned confidence interval does not contain zero, the effect is considered to be statistically significant. During the regression analysis, age was specified as the independent variable, GAI usage was specified as the dependent variable, while technostress was specified as the mediator.

Results

Descriptive statistics & correlations

The descriptive statistics and Pearson correlations were calculated for all variables of interest and displayed in Table one below. Age showed no significant correlation with GAI usage ($r = -.100, p = .176$), nor with technostress ($r = .006, p = .931$). Furthermore, there was a significant positive correlation found between technostress and GAI usage ($r = .152, p = .040$), suggesting that there is a correlation between increased technostress and higher GAI usage.

Table 1.

Descriptive statistics and Pearson correlations

	Mean	SD	N	α	1	2	3
<i>Age</i>	36.19	10.25	185	—	—		
<i>Technostress</i>	2.06	0.820	185	.846	.006	—	
<i>GAI Usage</i>	2.31	0.750	185	.907	-.100	.152*	—

*Note: * $p < .05$*

Assumption checks & reliability analyses

Barlett's Test of Sphericity and the KMO measure of sampling adequacy were done when analysing the items of the construct GAI usage. The former was significant ($<.001$), while the latter had a value of .871, thus fulfilling the assumptions of an EFA. From the scree plot and total variance explained tables, three principal components were extracted, which cumulatively explained 60.169% of the variance. For this thesis, as the items are from an unpublished manuscript, the items may not be published in this thesis, which also entails that elaborating on these factors would inadvertently disclose these items. To maintain the simplicity of the model and not cause confusion with components that have not been theoretically underpinned, GAI was

treated to consist of one component. As for the scale's reliability, Cronbach's Alpha was found to be .907, which indicates that the scale is reliable.

Regarding technostress, Barlett's Test of Sphericity and the KMO measure of sampling adequacy were again tested, with the former being significant, while the latter had a value of .823, thus once more fulfilling the assumptions of an EFA. From the scree plot and total variance explained tables, one principal component was extracted, which explained 62.906% of the variance. As for the scale's reliability, Cronbach's Alpha was found to be .846, which indicates that the scale is reliable.

Hypothesis testing

To test the hypotheses, simple linear regression was used for the first three hypotheses, while the SPSS PROCESS model V4.2 was used to test H4. The results of these analyses are shown below in Table 2. The output of the PROCESS model can be found in appendix A.

H1. Age is negatively associated with Generative AI usage

This hypothesis was found to be statistically insignificant, $F(1, 183) = 1.85, p = .176$, with age only explaining 1% of the total variance in GAI usage ($R^2 = .010$). The regression coefficient between age and GAI usage was also found to be statistically insignificant ($B = -.007, p = .176$), and as such, H1 is not supported by the data.

H2. Age is positively associated with technostress

This hypothesis was found to be statistically insignificant, with the regression coefficient between age and technostress also being insignificant ($B = .001, p = .931$), and as such, h2 was not supported by the data.

H3. Technostress is negatively associated with Generative AI usage

This hypothesis was found to be statistically significant, with technostress explaining 2.3% of the total variance in GAI usage ($R^2 = .023$). However, the regression coefficient between technostress and GAI usage was found to be positive and statistically significant ($B = .138, p = .40$), which indicates that higher levels of technostress can be associated with increased GAI usage. This means that while there was a significant positive relationship between technostress and GAI usage, H3 is rejected, due to it arguing a negative association.

H4. The negative relationship between age and generative AI usage is mediated by technostress.

The total effect of age on GAI usage was found to be statistically insignificant ($B = -.0073, p = .18$). The direct effect of age on GAI usage, while controlling for technostress, was also statistically insignificant ($B = -.0074, p = .17$). The indirect effect through technostress was negligible ($B = <.001$), with a 95% confidence interval of $[-0.0015, 0.0019]$, which falls between. As such, the mediation effect (H4) was not statistically significant.

Model summary

Thus, hypotheses one, two, and four were rejected, while hypothesis three was accepted. Overall, the model only accounted for a small portion of the variance in GAI usage ($R^2 = .033$), which suggests that additional factors, which were not examined in this study, could play a larger role in predicting the usage of GAI technology.

Table 2.

Summary of Linear Regression Analyses (H1-H3)

Hypothesis	Predictor	Outcome	B	SE	β	t	p	R ²
H1	Age	GAI usage	-.007	.005	.100	-.100	.176	.010
H2	Age	TS	.001	.006	.006	.006	.931	.000
H3	TS	GAI usage	.138	.067	.152	2.07	.040*	.023

Note: N=185

* $p < .05$

Discussion

This thesis investigated the relationship between age and GAI usage, and the mediating effect of technostress. The literature on the relationship between age and GAI usage is very limited, especially when considering the possible role of technostress, a gap that this thesis addressed.

The questionnaire from which the data was taken included 184 participants. This data was analysed at the individual level. From the analyses, only one significant effect was found, in the relationship between technostress and GAI usage, but as a result of the respective hypothesis arguing an opposite association, hypothesis three was not accepted. All other effects were found to be insignificant, and as such, hypotheses one, two, and four were not accepted. This means that there was no significant effect between age and GAI usage, age and technostress, as well as no mediation effect of technostress in the relation between age and GAI usage. There does appear to be a significant positive effect between technostress and GAI usage, based on the findings from this study.

The first hypothesis was rejected. This hypothesis proposed that age had a negative association with GAI usage. However, the data contested this, showing no significant correlation

between the two. As such, the data suggests that age does not influence the amount of GAI that is used by an individual. Although this hypothesis was based on previous literature that suggest that older generations adopt more slowly to new technologies (Afzal et al., 2023; McFarland, 2001), the data showed that that was not the case in this study. A plausible interpretation of this would be that the rapidly increasing ease of access to GAI tools has lowered the technological barrier and as a result has made usage less dependent on digital literacy by age (Bright et al., 2024; Nah et al., 2023). Moreover, while previous research by Çoklar and Tatli (2021) and Van Dijk (2012) highlighted the digital divide between older and younger generations, the ever-more present use of digital technologies, such as GAI, in the workplace could have lessened the effect of generational differences. This would hold especially true for those who are highly educated, such as is the case in the sample for this study. Therefore, age may not play as pivotal a role when it comes to GAI usage as was hypothesised.

Furthermore, hypotheses two was also rejected. This hypothesis proposed that those with a higher age would experience more technostress. In contrast to previous literature by Ning and Alikaj (2018) and Setyadi et al. (2017), who's research suggested that older generations are more likely to view technology as a hindrance demand, and as a result report higher levels of stress due to lower digital literacy, the data in this study did not support this hypothesis. A possible explanation can be found by going through the mixed findings in other previous studies. Two such examples are Mahapatra and Pillai (2018) and Marchiori et al. (2019), who found that the effect of age on technostress differs substantially based on the context the study finds itself. Factors such as industry, perceived organisational support and the extent to which the technological landscape within an organisation is developed substantially impact the way technostress is experienced by individuals of different age groups. In addition, Hauk et al. (2019)

found that older workers do not necessarily use less coping mechanisms, but cope differently than younger workers, and tend to use less dysfunctional coping mechanisms than their younger counterparts. Thus, they experience, and deal with stressors differently. This could explain why the amount of technostress they experience is less affected by their age than proposed by the hypothesis. Subsequently, this suggests that age may not explain differences in technostress, and that other factors such as coping styles, technological environments and personal attitudes could instead play a more critical role.

The third hypothesis stated that there was a negative association between technostress and GAI usage and was rejected. This is in contrast to previous research, that argued that technostress could decrease the engagement and use of technology and GAI (Chang et al., 2024; Tarafdar et al., 2015). Technostress, when specifically linked to AI has been shown to reduce adoption intentions and instead lead to an increase in disengagement (Zhang & Tong, 2024), a finding this study contradicts. Understanding why this occurred might be crucial when trying to integrate GAI tools within an organisation. A study by Zhang et al. (2024) found that the dependency and usage of GAI was positively correlated with stress, indicating that higher levels of stress could lead to an increase in GAI usage.

This sentiment is in line with the fundamentals of the JDR, which shows that in order to deal with challenging demands, proper resources must be provided to in- and extrinsically motivate employees (Kim & Christensen, 2017). Those without them will fail to properly utilise the tools at their disposal (Kim & Christensen, 2017; Zhang & Tong, 2024), in this case leading to the improper use of GAI tools due to increased stress.

Lastly, hypothesis four was rejected. This hypothesis stated that the negative association of age with GAI was mediated by technostress. When looking at the mediation model, both the

direct and indirect paths from age to GAI usage were not statistically significant. This finding is in line with both hypotheses one and two not being supported, and reflects that age is most likely not a critical indicator of both GAI usage and technostress, as shown in this sample. This could mean that there are other variables that were not tested in the questionnaire that might play a more pivotal role in predicting these variables. Some conceptually applicable constructs could be digital literacy, openness to technology adoptions, or previous IT or AI experience. In line with warnings by Bernerth and Aguinis (2016), overattributing variance to demographic characteristics such as age could prove limiting when contextual and psychological variables may contribute more explanatory power. Similarly, Pansini et al. (2023) highlight that technostress arises due to the interaction between demands and resources. As such, age, as a static demographical variable, could only influence technostress in combination within specific contexts.

Theoretical implications

The foundations of this thesis were theoretically grounded in the Job Demands Resources (JDR) model (Demerouti et al., 2001). This model states that job demands can lead to strain and withdrawal behaviours when not supplemented with proper resources (Demerouti et al., 2001). Within this thesis, Age was thought to be a demand that would limit the usage of GAI. Technostress was thought to be a demand that would decrease usage of GAI due to being a stressor but seemingly increased the use of GAI. This study contributes to the very limited existing literature on the topic of GAI usage by investigating the role that of age and technostress play when considering the elements of this framework. These elements were rarely investigated in previous studies, and even more rarely were both investigated in the same study, leading to mixed findings and somewhat confusing perspectives on how age and technostress influenced

GAI usage, and how age and technostress affect the resource-demand relationships (Afzal et al., 2023; Chan & Lee, 2023; Chang et al., 2024; Hauk et al., 2019; Mahapatra & Pillar, 2018; Tarafdar et al., 2015; Zhang & Tong, 2024). Investigating these elements filled in these gaps and increased the understanding of GAI usage, and its relationships with both age and technostress.

In contrast to theoretical expectations, technostress did behave as a demand but lead to an increase in the use of GAI. This opposes findings by Pansini et al. (2023) and Tarafdar et al. (2015) who argued that that ICT stress, such as technostress, act as a demand and drain autonomy and engagement with tools. From the perspective of the JDR, this highlights the dual role of GAI tools, with them simultaneously being perceived as demands, but also as imposed resources, in this case leading to an increase in usage while experiencing technostress.

Furthermore, the findings indicated there to be no effect of age on technostress, which contradict one of the assumptions derived from the JDR by previous research, which is that older generations experience greater strain due to reduced technological capability (Çoklar & Tatli, 2021; Ning & Alikaj, 2018; Nimrod, 2018; Setyadi et al., 2017). The findings are, however, in line those of Hauk et al. (2019), that suggest that age may not be a reliable predictor of resource availability and usage, and that coping styles and perceived organisational support may be more valuable predictors of technostress. This study contributes to this understanding by affirming age does not necessarily play a role when predicting resource usage, in this case usage of GAI.

The findings from this study suggest using a static demographic characteristics like age may be better suited as control variables, with the independent variable being conceptionally more closely related to GAI, such as (digital) self-efficacy, perceived autonomy, or perceived organisational support. Furthermore, this thesis showed that while there is no negative association between technostress and GAI usage, there is a positive association, which could

prove useful when interpreting the effects of stress on GAI usage and conceptually similar constructs like GAI dependency or GAI reliance.

Practical implications

When it comes to practical implications an important thing to remember, is that insignificant relationships are results too. Finding that age was not a substantial predictor of GAI usage and technostress showed that other factors might be more valuable to consider when trying to predict these variables. Subsequently, when developing policies that deal with GAI, policymakers could take this finding into account in the development phase of these policies.

Furthermore, finding that technostress actually increased the usage of GAI showed that individuals might use GAI technology more, even when experiencing stressors caused by technology. This could be indicative of people relying on GAI because of their workload, especially when they can use GAI to decrease that workload by letting it take over menial or simple tasks.

Similar factors arose in interviews held with two HR-practitioners. The summaries of these interviews can be found in Appendix B. The HR employee and planner stated that generative AI was used by employees of all ages. They stated that while the adoption was a bit slower for some people, that slowed adoption was not specific to age, but more on a case-by-case situation. Some had previous ICT experience and felt more comfortable including GAI in their workflows, while others experienced a bit more of a hurdle when trying to effectively leverage the available tools. This is in line with the findings from this study, showing that age does not play a large role in the adoption and usage of GAI tools.

The HR consultant at a medical care provider highlighted that, even though they did not have an in-house GAI tool like some other organisations due to the sensitive nature of their

work, outside of matters that dealt with private company data, a lot of their employees used GAI as a tool to lighten their workloads. When asked about their sentiment towards AI tools, the interviewee mentioned that they think that there is definitively a place for these tools in the workplace, but that its usage should be very carefully regulated, to ensure data privacy. This highlights some of the anxiety that employees feel around using AI.

With this in mind, integrating these insights when dealing with GAI in the workplace might prove useful in overcoming these hurdles, and improving overall organisational performance and employee wellbeing. However, there are factors to consider when integrating it into the workplace, such as legislation on data privacy, and managing AI-anxiety among employees.

Limitations and suggestions for future research

This thesis includes several limitations that need to acknowledge to ensure transparency. Clearly considering and articulating limitations in research helps to contextualise the findings, as well as support the integrity of the research process. Furthermore, including the limitations enables future researchers create apt methodological approaches and build on current practices to further the understanding of the research topic. (Ross & Zaidi, 2019).

The first limitation is that the data used in this thesis came from a questionnaire that was one taken once, making it cross-sectional. As a result, while the results may accept or reject the hypotheses in this case, in another setting the results might have differed. Future studies could benefit from using a longitudinal or an experimental design to analyse how the construct interact over a span of time and to ascertain causality more precisely.

Secondly, as all data was self-reported, it makes the study vulnerable to social desirability bias and response bias: some respondents could have under- or over-reported their GAI usage or

their perceived stress levels, whether it was a conscious choice or an unconscious one (Rosenman et al., 2011). Rosenman et al. (2011) also found that even while anonymity was assured, the possibility of misreporting is still a risk, whether it happens unintentionally or due to social desirability bias. As such, participants misreporting their stress levels or GAI usage patterns, should still be a factor that needs consideration. Future researchers could mitigate this by using multi-method data collection, like using logging files, system analytics, and self-reporting to increase the validity of their measures.

As for the third limitation, due to age being the independent variable, this thesis did not include control variables such as gender or industry type. This was a conscious decision, due to the nature of age as a static demographic variable, the risk of overcontrolling, and to preserve theoretical clarity and the variance that is attributed to age (Bernerth & Aguinis, 2016; Li, 2021). However, for the sake of transparency, it has to be acknowledged that this approach may have left out other valuable contributors that explained GAI usage and/or technostress. Rather than using age as an independent variable, future studies might consider using it as a control variable and instead focus on independent variables that are conceptually closer to GAI usage. Psychological or organisational factors such as (digital) self-efficacy, perceived autonomy, or perceived organisational support may provide a more exact understanding of how individuals perceive and utilise GAI tools. Furthermore, technostress was shown to have a positive association with GAI usage, a relationship that merits further investigation to discover underlying factors and possible consequences.

Finally, the construct of GAI usage was measured using a 13-item scale taken from an unpublished manuscript. Although the scale showed internal consistency within the data analyses, the lack of a formal peer-review invites uncertainty when it comes to validity,

dimensionality, reproducibility, and cross-sample applicability (Ceci & Peters, 1982). Because this scale has yet to be validated, it is possible that it does not contain all valuable dimensions of GAI usage. As such, validating this scale across different settings and comparing it to other measures to ensure generalisability could prove useful for future research.

Conclusion

This thesis aimed to explore the relationship between age and the usage of generative artificial intelligence, with technostress being proposed as a potential mediator. Theoretically framed within the perspective of the Job-Demands-Resources model, this thesis attempted to establish whether differences in age influenced technostress and caused variations in GAI usage. GAI tools have become increasingly commonplace in the professional environment over the past years, and as such it was deemed a worthy topic to investigate.

The findings showed that there was no statistically significant relationship between age and either technostress or GAI usage, which resulted in the mediation hypotheses not being supported. The results suggest that age is not an antecedent of how employees experience technostress, or how they interact with GAI. However, a small, but statistically significant positive association was found between technostress and GAI usage, which suggested that individuals might use GAI tools, even whilst they experience strain. This, over an extended period of time, could result in burnout, and other wellbeing concerns.

Theoretically, this thesis contributed to the understanding of GAI usage and adoption, indicating that the traditional assumption, that older generations prefer to distance themselves from the digital landscape, may be outdated and oversimplified. Practically, this thesis suggests that organisations should centre their strategies and policies more around providing adequate

personal resources, and less on mitigating generational differences, when it comes to the integration of GAI tools in the workplace.

With GAI tools and technologies becoming evermore prevalent in the workplace, influencing and transforming operations and previously established methodologies, ensuring that employees can engage with these tools efficiently is vital. Technology is the future, whether we like it or not. Creating guidelines that foster our own critical thinking skills and emphasize the use of tools, as just that, is the responsibility of those who claim to ethically and responsibly engage with technology.

A GAI tool should be just that, a supplement to our own cognition, regardless of our age. Nothing more.

References

- Aguinis, H., & Bradley, K. J. (2014). Best practice recommendations for designing and implementing experimental vignette methodology studies. *Organizational research methods, 17*(4), 351-371.
- Alhaffar, M. B. A., Abbas, G., & Alhaffar, M. A. A. (2019). The prevalence of burnout syndrome among resident physicians in Syria. *Journal of Occupational Medicine and Toxicology, 14*. <https://doi.org/10.1186/s12995-019-0250-0>
- Ali, H., Mustafa, A. u., & Aysan, A. F. (2025). Global adoption of generative AI: What matters most? *Journal of Economy and Technology, 3*, 166-176.
<https://doi.org/https://doi.org/10.1016/j.ject.2024.10.002>
- Atrian, A., & Ghobbeh, S. (2023). Technostress and job performance: Understanding the negative impacts and strategic responses in the workplace. *arXiv preprint arXiv:2311.07072*.
- Bandura, A. (1999). Social cognitive theory: An agentic perspective. *Asian journal of social psychology, 2*(1), 21-41.
- Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual review of psychology, 52*(1), 1-26.
- Bandura, A., & Wessels, S. (1997). *Self-efficacy*. Cambridge University Press Cambridge.
- Bernerth, J. B., & Aguinis, H. (2016). A critical review and best-practice recommendations for control variable usage. *Personnel psychology, 69*(1), 229-283.
- Bharadiya, J. P., Thomas, R. K., & Ahmed, F. (2023). Rise of artificial intelligence in business and industry. *Journal of Engineering Research and Reports, 25*(3), 85-103.

- Boonjing, V., & Chanvarasuth, P. (2017). Risk of overusing mobile phones: Technostress effect. *Procedia computer science, 111*, 196-202.
- Brod, C. (1984). Technostress: The human cost of the computer revolution. *(No Title)*.
- Chan, C. K. Y., & Lee, K. K. (2023). The AI generation gap: Are Gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and millennial generation teachers? *Smart learning environments, 10*(1), 60.
- Chang, P.-C., Zhang, W., Cai, Q., & Guo, H. (2024). Does AI-Driven technostress promote or hinder employees' artificial intelligence adoption intention? A moderated mediation model of affective reactions and technical self-efficacy. *Psychology Research and Behavior Management, 413-427*.
- Çoklar, A. N., & Tatli, A. (2021). Examining the Digital Nativity Levels of Digital Generations: From Generation X to Generation Z. *Shanlax International Journal of Education, 9*(4), 433-444.
- Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied psychology, 86*(3), 499.
- Felemban, H., Sohail, M., & Ruikar, K. (2024). Exploring the Readiness of Organisations to Adopt Artificial Intelligence. *Buildings, 14*(8), 2460.
<https://doi.org/10.3390/buildings14082460>
- Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative ai. *Business & Information Systems Engineering, 66*(1), 111-126.
- Foster, S., Pangle, A., Schrader, A., Wei, J. Y., & Azhar, G. (2016). Adaptations in the age of technology in seniors. *Gerontologist, 56*(3), 528.

- Fui-Hoon Nah, F., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023). Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. In (Vol. 25, pp. 277-304): Taylor & Francis.
- Georgescu, R. I., & Bodislav, D. A. (2024). The generational divide-A debate on technology and the decision-making process. *Theoretical & Applied Economics*, 31(2).
- Ghasemaghaei, M. (2020). The role of positive and negative valence factors on the impact of bigness of data on big data analytics usage. *International Journal of Information Management*, 50, 395-404. <https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2018.12.011>
- Gragnaniello, D., Marra, F., & Verdoliva, L. (2022). Detection of AI-generated synthetic faces. In *Handbook of digital face manipulation and detection: From deepfakes to morphing attacks* (pp. 191-212). Springer International Publishing Cham.
- Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford publications.
- Kim, S., & Christensen, A. L. (2017). The dark and bright sides of personal use of technology at work: A job demands–resources model. *Human Resource Development Review*, 16(4), 425-447.
- La Torre, G., Esposito, A., Sciarra, I., & Chiappetta, M. (2019). Definition, symptoms and risk of techno-stress: a systematic review. *International archives of occupational and environmental health*, 92, 13-35.
- LeBlanc, V. R. (2009). The effects of acute stress on performance: implications for health professions education. *Academic Medicine*, 84(10), S25-S33.

- Li, M. (2021). Uses and abuses of statistical control variables: Ruling out or creating alternative explanations? *Journal of Business Research*, *126*, 472-488.
<https://doi.org/https://doi.org/10.1016/j.jbusres.2020.12.037>
- Lozoya, S. V. M., Guirado, M. A. Z., González, A. Z., & López, A. B. M. (2022). Use of technologies and self-efficacy in older adults. *IEEE Revista Iberoamericana de Tecnologías Del Aprendizaje*, *17*(2), 125-130.
- Malka, S. C., MacLennan, H., & De Queiroz, H. (2025). Measuring the impact of AI-related Attitudes, Awareness, Skills and Usage on Students' Learning Experience: A Gender-based Exploration. *Awareness, Skills and Usage on Students' Learning Experience: A Gender-based Exploration (March 12, 2025)*.
- McFarland, D. J. (2001). The Role of Age and Efficacy on Technology Acceptance: Implications for E-Learning.
- Miyazaki, K., Murayama, T., Uchiba, T., An, J. S., & Kwak, H. (2024). Public perception of generative AI on Twitter: an empirical study based on occupation and usage. *Epj Data Science*, *13*(1), Article 2. <https://doi.org/10.1140/epjds/s13688-023-00445-y>
- Morris, M. G., & Venkatesh, V. (2000). Age differences in technology adoption decisions: Implications for a changing work force. *Personnel psychology*, *53*(2), 375-403.
- Nimrod, G. (2018). Technostress: measuring a new threat to well-being in later life. *Aging & mental health*, *22*(8), 1086-1093.
- Pang, C., Collin Wang, Z., McGrenere, J., Leung, R., Dai, J., & Moffatt, K. (2021). Technology adoption and learning preferences for older adults: evolving perceptions, ongoing challenges, and emerging design opportunities. Proceedings of the 2021 CHI conference on human factors in computing systems,

- Pansini, M., Buonomo, I., De Vincenzi, C., Ferrara, B., & Benevene, P. (2023). Positioning Technostress in the JD-R Model Perspective: A Systematic Literature Review. *Healthcare, 11*(3), 446. <https://doi.org/https://doi.org/10.3390/healthcare11030446>
- Popescu, I. M., Zavatin, I., Manea, D. I., Pamfilie, R., & Jurconi, A. (2024). Adapting the Competences of the Employed Personnel in the Context of the Integration of Artificial Intelligence in Organisations. *Amfiteatru Economic, 26*(67), 817-831.
- Rahman, M. M., Babiker, A., & Ali, R. (2025, 2025//). Motivation, Concerns, and Attitudes Towards AI: Differences by Gender, Age, and Culture. *Web Information Systems Engineering – WISE 2024, Singapore.*
- Reddy, P., Sharma, B., & Chaudhary, K. (2020). Digital Literacy: A Review of Literature. *International Journal of Technoethics (IJT), 11*(2), 65-94. <https://doi.org/10.4018/IJT.20200701.oa1>
- Rosenman, R., Tennekoon, V., & Hill, L. G. (2011). Measuring bias in self-reported data. *International Journal of Behavioural and Healthcare Research, 2*(4), 320-332.
- Ross, P. T., & Bibler Zaidi, N. L. (2019). Limited by our limitations. *Perspectives on medical education, 8*, 261-264.
- Schaufeli, W. B., & Bakker, A. B. (2004). Job demands, job resources, and their relationship with burnout and engagement: A multi-sample study. *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior, 25*(3), 293-315.
- Schlögl, S., Postulka, C., Bernsteiner, R., & Ploder, C. (2019). Artificial intelligence tool penetration in business: Adoption, challenges and fears. *Knowledge Management in*

- Organizations: 14th International Conference, KMO 2019, Zamora, Spain, July 15–18, 2019, Proceedings 14,
- Song, X. H., Xu, L. C., Peng, C. Y., Pan, S., Adibi, A., Wang, X. R., & Lu, Z. L. (2025). Enhanced creativity at the cost of increased stress? The impact of generative AI on serious games for creativity stimulation. *Behaviour & Information Technology*.
<https://doi.org/10.1080/0144929x.2025.2459267>
- Tagurum, Y., Okonoda, K., Miner, C., Bello, D., & Tagurum, D. (2017). Effect of technostress on job performance and coping strategies among academic staff of a tertiary institution in north-central Nigeria.
- Tarafdar, M., Pullins, E. B., & Ragu-Nathan, T. (2015). Technostress: negative effect on performance and possible mitigations. *Information systems journal*, 25(2), 103-132.
- Urick, M. (2017). Adapting training to meet the preferred learning styles of different generations. *International Journal of Training and Development*, 21(1), 53-59.
- Urukovičová, N., Rošková, E., Schraggeová, M., & Smoroň, J. (2023). Psychometric properties of the Technostress Creators Inventory among employed Slovak respondents. *Computers in Human Behavior Reports*, 12, 100324.
- Wang, Q., & Yao, N. (2025). Understanding the impact of technology usage at work on academics' psychological well-being: a perspective of technostress. *BMC psychology*, 13(1), 130.
- Wang, X., Li, Z., Ouyang, Z., & Xu, Y. (2021). The Achilles heel of technology: how does technostress affect university students' wellbeing and technology-enhanced learning. *International Journal of Environmental Research and Public Health*, 18(23), 12322.

- Yi, Y., Wu, Z., & Tung, L. L. (2005). How individual differences influence technology usage behavior? Toward an integrated framework. *Journal of Computer Information Systems*, 46(2), 52-63.
- Zajacova, A., Lynch, S. M., & Espenshade, T. J. (2005). Self-Efficacy, Stress, and Academic Success in College. *Research in Higher Education*, 46(6), 677-706.
<https://doi.org/10.1007/s11162-004-4139-z>
- Zhang, T., & Tong, Q. (2024). The Technostress of ChatGPT Usage: How Do Perceived AI Characteristics Affect User Discontinuous Usage Through AI Anxiety and User Negative Attitudes? *International Journal of Human-Computer Interaction*, 1-12.

Appendices

Appendix A - PROCESS SPSS Mediation Analysis results

Results of Mediation Analysis Using Model 4 of PROCESS Macro

	Total effect (SE)	Direct effect (SE)	Indirect effect through technostress
Age	-0.007 (0.005)	-0.007 (0.005)	0.000 (0.001)
% of the total effect	-	98.6%	1.4%

Note. N= 185

Note. The percentages were calculated based on the 4 decimal answers

* $p < 0.05$

Appendix B – Interviews with HR Professionals

Interview with an HR-employee and Planner

After asking for consent for the interview, the interviewee was asked to provide some insight into the integration of generative AI in the workplace. He is an HR employee and planner at a multinational retail and wholesale holding company.

After the topic introduction, the interviewee immediately shared his experiences with GAI in the workplace. He mentioned that they are definitely being used by a lot of people. He mentions that they operate in a very large-scale operational setting and are in contact with countless people. He notes that nearly everyone uses GAI tools, across all age groups. He jokes that even those close to retirement age have taken an interest in AI, as they just want to do less. After being probed for this, he says that “there is a perception that older employees struggle more with adopting to these generative AI tools, but I honestly don’t think that’s really the case.

They have made it really easy to understand, and even if someone doesn't understand, they can just ask the AI to explain!"

According to the interviewee, GAI is currently being used in different ways by different people across the different departments within the organisation. Some use it to assist in creating emails, summarise meeting notes or even create templates for training materials. He mentions that it's mostly being used to save time and get all those repetitive administrative tasks over with. He says that with those out of the way, people can actually focus on the meaningful tasks, which he thinks is a good thing. However, he does caution about the privacy of internal data and personnel data. The organisation employs a lot of people and is thus responsible for safeguarding their information.

When asked how they generally feel about GAI, he mentions that he thinks it's a good thing that they are able to use it for the simple tasks that don't really require a lot of thinking, but that when it comes to the big decisions, he feels that it should definitely still be an expert making those. He goes on to say that he doesn't fear for his position being taken over by AI, as he needs to make decisions regarding people, and "that's just not something they can trust a computer program with". He says that there are some people who will probably be replaced, but that those people will probably be relocated to other positions where they can be more useful. If their entire job was so easy that it could be automated, then that's for the best.

Interview with an Ex-HR-consultant at a global health care provider

After asking for consent for the interview, the interviewee was asked to provide some insight into the integration of generative AI in the workplace. He worked as an HR consultant at a global provider of medical care. He was asked to provide his perspective on GAI considering his time there. The interviewee started by acknowledging that the organisation did not yet have an in-

house GAI tool. This decision was made as they did not feel comfortable just using an open sourced LLM to handle sensitive information. Furthermore, the activities of the health care provider are very tightly regulated, and they adhere to a lot of legislation to ensure customer privacy. They explained that while they recognise the potential of GAI tools as a possible helping hand, the concerns of data privacy trumped their interest in ‘trying a new toy’. The interviewee stated that they operate in a sector where any leak or misuse of information could have massive consequences, as well as cost them clients, business licences, and the possibility of being drawn into lawsuits. He half-jokingly stated that until they are absolutely sure that the usage of such tools complies with medical confidentiality standards, they won’t be touching it with a thirty-nine-and-a-half-foot pole.

When asked about their general sentiment towards GAI in the workplace, the interviewee answered that he thinks there is definitely a place for them, as they can support employees in handling menial tasks, but that that doesn’t mean they should go headfirst into using the tools without establishing a proper plan first. He once again underlined it by referring to the data safety concerns. He feels that without a proper plan and safety checks, using GAI haphazardly could lead to data breaches, people pointing fingers at an entity that has no accountability, and the spreading of misinformation. He feels that yes, it can be useful, but ultimately any and all decision-making should be done by a real person with real critical thinking skills.

Afterwards, this was followed up by a question about those ‘real people’. When asked how they felt about possible AI integration in the workplace, the interviewee took a cautious stance. He mentioned that some of his colleagues expressed feelings of anxiety and unease when discussing the ever-growing role of AI, knowing that it would one day be their turn as well. He mentioned that they sometimes did not know what they could, and couldn’t, use GAI for. And on

a deeper level, some feared that their jobs might be replaced by it entirely. The interviewee thinks that this anxiety reflects the constantly growing tension between technological innovation and human job security. He emphasizes that this is especially the case in countries where healthcare is privatised, and big corporations may want to save money by using AI, but where human judgement and decision-making is as crucial as it gets.

He rounded his statement up by saying that he does feel optimistic about the future, even considering AI, but that we, as a society, should err on the side of caution. GAI might be able to reduce certain workloads and make some workflows more efficient, but we can't simply implement it without ensuring we have safeguards and meticulous human verifications.