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Cognitive Performance in the Digital Era:

Generational Differences, Stress, and Distraction's Impact on Cognitive Performance

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ABSTRACT

Generational categories classify individuals born in specific time frames, known for unique traits and tech adaptability. Some research indicates that the digital-native generation is more prone to distractions than other groups. However, the underlying mechanism is unclear and influenced by many factors, such as stress. In the current study (n=299), the authors leveraged the mobile monitoring of cognitive change (M2C2) symbol search task to measure processing speed. This study examines the relationships between generational categories (Gen X, Millennials, and Gen Z), perceived stress, subjective age (considered to predict important aspects of well-being beyond chronological age), and distraction cost. These results emphasize the significant influence of age-related variables and stress in shaping susceptibility to distractions. Future research can expand participant numbers, conduct longitudinal studies to track cognitive changes in digital-era generational cohorts, and explore neurocognitive mechanisms and technological fluency's role in distraction susceptibility.

KEYWORDS

cognitive, digital, distraction cost, Gen X, Gen Z, Millennials, stress, subjective age

INTRODUCTION

Generational thinking – comparing cohorts based on ranges of year of birth – implicitly assumes that individuals born within the same timeframe or generational cohorts tend to share common values and characteristics, such as beliefs, motivations, values, and behaviors, that set them apart from individuals born in different eras (Mitchell, 2003). As people are born between specific years, generations are frequently described by labels (Raphelson, 2014). There are several general categories, such as Baby Boomers (born between 1946 and 1964), Generation X (born between 1965 and 1980), the Millennial generation (born between 1981 and 1996), and Generation Z (born in 1997 onward) (Pew Research Center, 2018).

In terms of engagement with technology, Gen X (and generations that preceded them) were not born into the digital world but adopted and adapted to new technologies later in life. These individuals

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did not have the privilege of growing up with technology as an inherent and integral aspect of their formative years. Instead, they have acquired technological proficiency during adulthood and late adulthood, in the case of Baby Boomers (Prensky, 2001). Members of Gen X did not have cell phones when they were growing up, took longer to adopt new technologies, experienced greater anxiety when using them, and used fewer different types of technologies (Volkom et al., 2014; Zickuhr & Madden, 2012; Olson et al., 2011). According to Calvo-Porral & Pesqueira-Sanchez (2019), Generation Xers' motivations for information searches impact their use and interaction with technology.

Millennials were the first generation to have computers in their schools, and they became adults when the internet became widely used and tried to adapt to many forms of digital technology and social media. Their generation could be called "digital natives" (Prensky, 2001; Palfrey & Gasser, 2013). Compared with Generation X, Millennials perceive information and communication technologies more positively (Howe & Strauss, 2003). They incorporate technology into their daily lives to stay connected to social networks, creating, and sharing information on their blogs or social media (Hershatter & Epstein, 2010; Noble et al., 2009). Additionally, some Millennials have acquired the multitasking skills necessary to balance their personal lives, careers, and online communication. They can work, study, and engage in online social networking simultaneously.

The next younger generation is Gen Z – individuals who grew up with mobile devices as a central aspect of their lives and have been exposed to technology from a very young age, making them true digital natives (Schroth, 2019). Compared to Millennials, Gen Z started connecting to the internet earlier, with smartphones as one of their first displays, making them a generation primarily focused on mobile devices. Gen Z individuals maintain a perpetual state of connectivity and prefer communication through technology, prioritizing digital interactions over face-to-face encounters. This characteristic reflects their inclination toward digital communication channels and their comfort with technology as a primary mode of engagement (Poláková & Klimova, 2019).

Each generation may have distinct online communication and interaction preferences. Younger generations, for example, may prefer text-based communication and social media platforms, whereas older generations may prefer email and phone calls. In general, younger generations are more technologically literate and accustomed, while older generations might take longer to become accustomed to and proficient in using new digital platforms and may have acquired digital skills through training. Older generations can overcome digital barriers and enhance their digital literacy and proficiency through various strategies, such as seeking help from tech-savvy friends and family, attending workshops, and practicing regularly. It is important to recognize that differences in technological comfort and competence can influence screen time usage patterns, resulting in various effects on various cognitive domains.

Screen Time, Cost of Distraction, and Processing Speed

"Screen time" refers to how much time a person spends interacting with screens, including those on televisions, computers, laptops, smartphones, tablets, and other digital devices. Screen time usage varies across age categories, with distinct patterns emerging among generations. Generation Z and Millennials have seamlessly integrated technology into their daily lives. They are known for their extensive use of digital devices, including smartphones, tablets, and computers, and are highly engaged with various forms of social media and apps (Shatto & Erwin, 2017). This tech-savvy behavior has led to a preference for multitasking and the ability to effortlessly switch between activities like instant messaging, web browsing, and gaming on their devices (Foehr, 2006). However, this convenience also comes with the challenge of constant digital distractions, making it difficult for these generations to sustain long-term concentration on a single task (Rosen, 2017). In contrast, older generations may exhibit more moderate screen time habits, emphasizing traditional communication methods like email and phone calls.

In the mobile world, individuals may experience "serial digital distraction" as they attempt to process the massive bits cascading to them. The constant distraction from digital devices will probably have detrimental effects on memory and learning (Junco & Cotten, 2011; Wood et al., 2012; Purcell et al., 2012). Frequent or extended screen time, encompassing activities like smartphone use, tablet and computer usage, and television watching, can place a substantial demand on attentional resources. These digital screens frequently display text, images, videos, notifications, and interactive elements. Individuals must allocate their attentional resources efficiently to navigate and process this information. Excessive screen time, particularly when characterized by constant multitasking and frequent interruptions, can result in attentional fatigue and decreased cognitive performance in tasks that require sustained focus and concentration. Individuals who struggle to control their attention are potentially more susceptible to distraction and processing speed problems (Lustig et al., 2006).

Furthermore, the constant exposure to visually stimulating and potentially distracting content on screens may impact an individual's ability to maintain focus and resist attentional capture by salient distractors in the environment (Theeuwes, 2023). Their attentional resources may be more susceptible to capture by sudden or eye-catching stimuli in their surroundings, which can lead to disruptions in their workflow or interactions. Exposure to distracting stimuli that capture their attention can lead to a diversion of cognitive resources away from the primary task at hand. Furthermore, this diversion can decrease processing speed, as the brain needs to reallocate its resources and switch tasks to address the distracting elements. The potential for distraction susceptibility also exhibits an age-related dimension, as younger individuals tend to be more deeply immersed in digital screen interactions than their older counterparts. The age-associated variation suggests the likelihood of differences in cognitive performance, particularly in processing speed.

Aging: Objective and Subjective Aging Processes Differ

Baltes and Lindenberger (1997) explain that a decrease in processing speed is related to the physiological architecture of the aging brain, which is closely associated with the aging process. However, this decline is not solely attributed to age but also influenced by interactions with environmental changes, potentially including distractions from technological developments in their era. These distractions contribute to variations in individual life courses. The digital era has introduced numerous cognitive distractions that compete for our attention during learning, recollection of past events, or solving complex problems. It is important to note that many cognitive processes are not solely innate but heavily influenced by environmental factors (Paus, 2005).

Furthermore, we considered involving subjective age in our analyses because while chronological age provides some information, some literature mentioned that it does not account for the wide variation in how people perceive their own aging and experience age-related processes (Diehl et al., 2014; Rubin & Berntsen, 2006). Hughes and Touron (2021) state that subjective age predicts important aspects of well-being beyond chronological age. Moreover, it is related to late-life health outcomes, including physical health (Stephan et al., 2012; Westerhof et al., 2014), depressive symptoms (Keyes & Westerhof, 2012), and cognitive decline (Stephan et al., 2014; Stephan et al., 2016a).

Based on these several findings, subjective age can influence various facets of life. For instance, older adults who perceive themselves as younger tend to exhibit better physical health, lower levels of depression, and slower cognitive decline. This intriguing relationship emphasizes the importance of subjective age as a potential modifier in the context of aging and cognitive processes. By considering subjective age alongside chronological age, we aim to obtain a more comprehensive understanding of how individuals' self-perceptions and experiences of aging contribute to cognitive outcomes, providing insightful information about the multifaceted nature of the aging process.

INVESTIGATION

Constant distractions disrupt our focus, but stress also plays a role. Perceived stress can also influence how people react to disruptions. When someone is already stressed, they may be more sensitive to distractions and find them more disturbing than when they are not. Stress reflects interactions between individuals and their environment, which they assess as threatening or taxing their resources in such a way as to affect their cognitive performance (Luck & Vogel, 2013; Owens et al., 2012; Storbeck, 2012; Sliwinski et al., 2006) and well-being (Lazarus & Folkman, 1984). This study aims to investigate distraction susceptibility within different generational categories and assess the impact of perceived stress on distraction costs. Generational categories would exhibit varying levels of distraction susceptibility, particularly interested in the potential influence of growing up in the digital age.

The present study examines the relationship between three generational categories (Gen X, Millennials, Gen Z) and perceived stress on the distraction cost of giving the correct responses as measured by the symbol search task. The study uses the three generational categories to represent or approximate the differences in how much exposure individuals from these generations have had to screens and technology throughout their lives. The assumption is that people from different generations have grown up in different technological eras, which may have influenced their technology use and screen time levels. Our research question driving this work is: How does distraction cost vary as a function of chronological age, subjective age, and perceived stress?

a. Hypothesis (RQ1): We expect a greater distraction cost in the youngest participants.
b. Hypothesis (RQ2): We expect a greater distraction cost in those who 'feel' youngest.
c. Hypothesis (RQ3): We expect a greater distraction cost in those who are most stressed.

Methods

Participants

This study is a cross-sectional study, and a total of 299 participants were recruited from the Prolific platform. Before beginning the trial, all subjects gave their informed consent. They were asked to fill out a collection of surveys (listed in the materials section) and complete web-based cognitive assessments (symbol search and grid memory task). Every participant received a $3 compensation for their active participation in the study, which typically took around 15 minutes to complete. In the study, participants are categorized into three generational groups. The age range spans 19 to 86 years (Mean=37.52, SD=12.17). For this study, we selected only three age categories (Gen X, Millennials, and Gen Z) because the sample distribution of Baby Boomers was too small, approximately only 5%.

MATERIALS

The survey encompassed a set of questionnaires, tasks, and demographic information, including chronological age and subjective age. The battery of questionnaires included assessments of the perceived stress scale (PSS), proximity risk factors (PRF), perceived discrimination scale (DISC), and daily inventory of stressful events (DISE). Participants also provided data on their ownership of various technology devices. For this manuscript, we are only focusing on demographic variables (age, subjective age), perceived stress (as measured by the perceived stress scale), and processing speed (as measured by the symbol search task).

M2C2Kit

The data for this study uses the M2C2Kit, which was last updated on August 23, 2023. M2C2Kit is a specialized library developed by the Ambulatory Methods for Measuring Cognitive Change research project, supported by the National Institute on Aging through Award #U2CAG060408. M2C2Kit is a versatile cognitive assessment tool developed in TypeScript. It leverages Google's canvas kit-wasm Skia-based graphics engine to deliver assessments through HTML5 and JavaScript. This versatility extends to user accessibility, as individuals can conveniently take assessments using either mobile or desktop web browsers. This adaptable approach ensures that cognitive assessments can be accessed and completed efficiently, easily accommodating users' preferences and device capabilities.

Symbol Search Task

An approach to measuring cognitive capacity involves the assessment of mental processing speed, typically by observing how efficiently individuals can perform a series of tasks with uncomplicated cognitive elements. The measurement of processing speed in humans takes place on at least three levels of description: psychometric tests, cognitive–experimental psychology, and psychophysics (Deary, 2000). In this study, we measured processing speed using psychometric tests, namely the symbol search task. Symbol search is a subtest of the Wechsler (1997) intelligence scales, widely used intelligence tests that assess cognitive abilities and intellectual functioning. The symbol search task assesses processing speed and visual scanning ability. This measurement is still frequently used to assess processing speed without considering potential aging-related decline, which is commonly linked to healthy aging (Seidler et al., 2002, 2010; Ebaid et al., 2017).

Participants are shown a series of symbols or simple geometric shapes with 20 trials – 10 trials with irrelevant signals (i.e., lure trials) and ten trials without such interference. Participants complete this task via a web browser of choice, delivered via M2C2Kit. During each trial, the upper part of the screen displays a row of three symbol pairs, and the lower part of the screen shows two symbol pairs to the participants (See Figure 1). Within a time limit, participants must scan the symbols and determine whether a specific target symbol is present among the symbols. The stimuli are displayed until a response is given, with a 200-millisecond pause between each response and the subsequent stimulus. The data is obtained as the median response time for correct trials. The median response time is a valid method for evaluating an individual's perceptual speed, which pertains to their capacity to promptly process and make judgments based on visual data, particularly when working with symbols or patterns (Sliwinski et al., 2018). It is anticipated that participants who complete the task more rapidly will demonstrate higher perceptual speed.

Figure 1. Display example

This symbol search task is given in the form of ambulatory cognitive assessments or evaluation of an individual's cognitive functions while they are in a mobile or real-life setting (Shiffman et al., 2008; Smyth & Stone, 2003) to provide a more ecologically valid picture of an individual's everyday behavior and cognitive functioning (Sliwinski et al., 2018; Fahrenberg et al., 2007).

Perceived Stress Scale (10-items)

The perceived stress scale (PSS) is a widely used self-report questionnaire to assess a person's perception of stress. Cohen et al. created it in 1983, and it has since become a standard stress assessment tool in clinical and research settings. In this study, we use the 10-item version of the PSS (Cohen & Williamson, 1988). The validity and reliability of the PSS-10 are also supported by psychometric data (Roberti et al., 2006). On a 5-point Likert scale, respondents are asked to rate how frequently they have experienced certain stress-related thoughts and feelings in the previous month, with options ranging from 0 (never) to 4 (very often). The PSS total score can range from 0 to 40, with higher scores indicating higher levels of perceived stress. Further, scores between 0 and 13 are regarded as low stress, scores between 14 and 26 as moderate stress, and scores between 27 and 40 as high perceived stress.

PROCEDURE

The survey begins with a consent question, where participants can consent or decline participation. The survey concludes if the participant declines. Those who consent proceed to provide demographic information, participate in cognitive tasks (symbol search and grid memory task), report recent stressful and uplifting events in DISE, and assess perceived stress with the PSS and proximity risk factors. Participants also share experiences of discrimination using the PSD and reveal their tech ownership and preferences. Each section is followed by time data recording. Participants are compensated through the Prolific platform.

In the study, we chose several variables, including chronological age, subjective age (participants' perceptions of their age), perceived stress (perceived stress levels over the past month), distraction cost (difference between the median response time correct lure and the median response time correct normal in the symbol search task)

Data Preparation

All data for surveys noted above were scored as per standardized scoring instructions noted in the primary source manuscripts. Qualtrics and R version 4.3.1 (and packages *dplyr, tidyverse,* and *ggplot2*) were used to prepare data. Age was categorized into three categories based on participants' birth years, which are Gen X (born 1965-1980), Millennials (born 1981-1996), and Gen Z (born 1997-2012). Next, for analysis, we divided the participants based on chronological age. The distraction cost in our study is quantified as the difference between task completion times when subjected to competing information or an irrelevant signal and task completion times without such interference, essentially calculated as the difference between response times for lure and normal trials in the correct answers.

Data Analysis

This study investigated how different age categories and perceived stress might affect distraction-related cognitive processes. Additionally, a hierarchical modeling approach was employed to determine the impact of various factors on the dependent variable. This approach involved three distinct steps or models. In the first step, the PSS was the sole predictor to model the dependent variable or distraction cost. In step 2, the model was extended to include both PSS and the participant's chronological age as predictors. In step 3, a more comprehensive model was constructed by introducing subjective age as an additional predictor.

Table 1. Descriptive statistics of each age category based on chronological age

	Gen X (N= 56)			Millennials (N= 152)			Gen Z (N=43)		
	Prop	M	SD	Prop	M	SD	Prop	M	SD
Chronological Age	22%	49.4	4.21	61%	33.3	4.26	17%	23.4	1.98

To assess the incremental contribution of each step in explaining the variance in the dependent variable, ΔR^2 (change in R-squared) was calculated at each stage of the analysis. ΔR^2 measures how much additional variation in the dependent variable is accounted for by including specific predictors. The values of ΔR^2 were examined to understand the influence of each added predictor. This hierarchical modeling approach allows for a step-by-step exploration of the factors contributing to distraction cost, providing valuable insights into the relative importance of these predictors in the context of the analysis.

RESULTS

Descriptive Statistics

Table 1 depicts information on the chronological age of the sample.

Table 1 shows that the proportion of each category (Gen X, Millennials, and Gen Y) is different based on chronological age. The Shapiro-Wilk test was then used to determine whether the data had a normal distribution, and the results show that data from each age category is not normally distributed.

Differences in Distraction Costs by Age Category and Perceived Stress

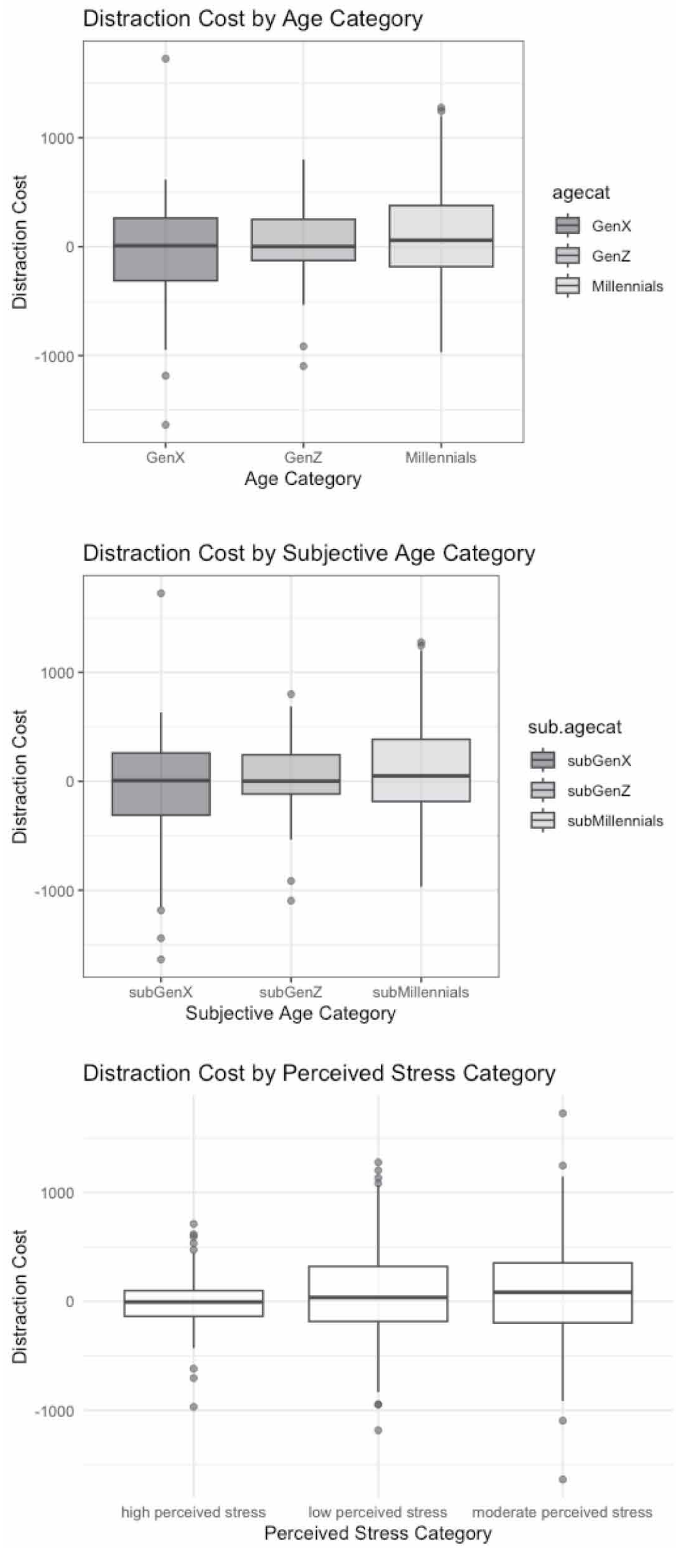
Using the Kruskal-Wallis (non-parametric test) to investigate potential differences in distraction costs across different age categories (chronological), we found no statistically significant differences in distraction costs among these age categories ($\chi^2 = 3.4482$, $df = 2$, $p = 0.1783$). In addition, differences in distraction costs across different subjective age categories also showed insignificant results ($\chi^2 = 3.148$, $df = 2$, $p = 0.207$). Furthermore, our analysis revealed no statistically significant variation across distraction costs by perceived stress level ($\chi^2 = 1.6838$, $df = 2$, $p = 0.4309$) (See Figure 2).

Hierarchical Regression

In the first analysis, the PSS was the sole predictor to model the dependent variable or distraction cost. It found that the PSS score was not a statistically significant predictor in explaining the variance in distraction cost (F (1, 296) = 1.797, $p = 0.1811$). In step 2, the model was extended to include both PSS and the participant's chronological age as predictors. The overall model was not statistically significant (F (2, 295) = 1.06, p = 0.3478), suggesting that the combination of perceived stress and chronological age did not significantly predict distraction cost. Further, in step 3, a more comprehensive model was constructed by adding subjective age as a predictor to the model in step 2. Similarly, the overall fit of the model did not reach statistical significance (F (3, 293) = 1.149, p = 0.3297). This suggests that the model with the perceived score, chronological age, and subjective age did not substantially improve its ability to account for the variance observed in the distraction cost.

Additionally, we examined the incremental contribution of variables at each step. The change in the coefficient of determination (ΔR^2) was assessed to gauge the added explanatory power of each step. When only the PSS score was included as a predictor, it accounted for a marginal increase in the proportion of variance explained, $\Delta R^2 = 0.0011$. The inclusion of age alongside perceived stress resulted in a further increase in R^2, $\Delta R^2 = 0.0045$, suggesting that age contributed to the model's explanatory power. Finally, when subjective age was added to the model in step 2, there was an additional increase in R^2, $\Delta R^2 = 0.0056$.

Figure 2. Differences in Distraction Costs by Age Category and Perceived Stress



DISCUSSION

Age Categories, Perceived Stress, and Cost of Distraction

Our results revealed no statistically significant differences in distraction costs among these age categories. Similarly, the findings also showed insignificant results when examining distraction costs across subjective age categories. Moreover, the analysis demonstrated no statistically significant variation in distraction costs by the perceived stress level. These results were somewhat unexpected and suggest that chronological age, subjective age, and perceived stress levels alone may not be the primary determinants of distraction costs in our sample. It might occur because of the unequal distribution between generational groups, and we only use the distraction cost based on the response time data on one task (symbol search).

However, based on our study's findings, we can understand the phenomena within the framework of cohort effects. According to epidemiologists, cohort effects are results that differ depending on the age at which a person is exposed to or susceptible to an event or cause (Keyes et al., 2010). From a sociologist's perspective, environmental factors affect a certain birth cohort's distinct birth group (Mason et al., 1973). In the study, the environmental factors are the role of technological advancements and variations in technology engagement. Generation X, Millennials, and Gen Z may have significant differences in their engagement with technology, and this reflects the unique technological environments that each cohort experienced during their formative years, ultimately influencing their attitudes and behaviors toward technology.

The outcomes for the individuals within the affected cohort may be short-lived or long-lasting because of these effects. In the study, the effect we want to examine is on cognitive performance, especially distraction costs or the difference between task completion times when subjected to competing information or an irrelevant signal and task completion times without such interference, essentially calculated as the difference between response times for lure and normal trials in the correct answers. We assume that age categories based on engagement with technological developments could have an impact on cognitive performance. These differences align with existing research that suggests variations in cognitive processing and multitasking abilities among different age groups (Minear et al., 2013). Generation Z and Millennials, who tend to integrate technology into their daily lives and are highly engaged with various forms of social media and apps (Shatto & Erwin, 2017), will likely face the challenge of constant digital distractions, making it difficult for them to sustain long-term concentration on a single task (Rosen, 2017). In contrast, older generations may exhibit more moderate screen time habits, enabling them to focus better on salient distractors than Gen Z and Millennials. Individuals who regularly engage in multiple forms of media use are worse or take longer to respond to tasks with salient distractors, possibly due to difficulties ignoring irrelevant stimuli.

In the context of attentional capture, it is essential to understand that salient distractors possess characteristics that make them particularly attention-grabbing, as described by Theeuwes (2023). These distractors are usually perceptually noticeable or unique, making them stand out from their surroundings. When these salient distractors automatically capture an individual's attention, they divert individuals from the primary task. In the symbol search task, salient distractors appear obvious. They may distract individuals, making them tend to choose the distractor option and taking them a long time to decide which answer is correct. Top-down cognitive processes can explain this phenomenon. When individuals possess top-down solid control, they can resist the pull of distractors and maintain focus on the primary task. Nonetheless, if individuals engage in prolonged screen time, particularly marked by persistent multitasking and frequent interruptions that involve numerous shifts between daily tasks, it can disrupt their ability to maintain attentional focus and render them more vulnerable to attentional capture. Incorporating the findings of Lustig et al. (2006), it is evident that individuals with difficulties controlling their attention may face challenges related to processing speed. The presence of distractions, coupled with limited attentional control, can lead to slower response times and reduced efficiency in cognitive tasks. However, we do not detect differences in distraction costs between age and stress categories in this study sample.

Furthermore, the hierarchical regression analysis aimed to assess the predictive power of perceived stress, chronological age, and subjective age in explaining variance in distraction costs. Initially, the PSS score was examined as the sole predictor but was not found to be a statistically significant predictor. Adding the chronological and subjective age as predictors also did not yield a statistically significant outcome. These findings suggest that the current set of predictors, individually or in combination, may not significantly contribute to explaining variation in distraction costs. The complexity of the relationship between these variables and distraction costs warrants further investigation to identify additional factors that better account for the observed variance, especially in normally distributed data.

Implication for Subjective Age vs. Chronological Age

Some literature mentions that age is a valuable construct in understanding distraction costs and individuals' self-perceived age play a more substantial role in explaining the observed variations in our data. Diehl et al. (2014) and Rubin and Berntsen (2006) note that chronological age provides some information. Still, it does not account for the wide variation in how people perceive their aging and experience age-related processes. Moreover, some studies examine how feeling younger or older than the actual age affects various outcomes. For instance, a study by Kwak et al. (2018) compared brain scans of healthy older adults and found that those who felt younger had more gray matter in certain brain areas, and their brains appeared younger, which could benefit their thinking abilities as they age. Additionally, younger subjective age has been linked to better cognitive abilities, according to Stephan et al. (2011). Older persons who felt younger than their chronological age showed higher long-term memory function and executive function ten years later, even after controlling for chronological age and other demographic and health characteristics (Stephan et al., 2018).

Nevertheless, further in-depth research in this area is warranted. We recommend investigating subjective age within specific contexts, as this approach may yield more nuanced insights. The impact of subjective age on various outcomes could differ based on the particular context being considered. For instance, individuals who feel younger in terms of their physical health might experience distinct effects on cognitive processing speed compared to those who feel younger primarily in the context of technology usage. Therefore, conducting targeted investigations within defined contexts can provide a more comprehensive understanding of how subjective age influences various aspects of individuals' lives.

Implications for Perceived Stress

Despite the absence of significant findings in our results, perceived stress might play a part in predicting distraction costs. Sliwinski et al. (2006) mention that individuals who frequently encounter stressful life events may not necessarily display cognitive impairment but may demonstrate decreased cognitive performance, particularly during periods shortly after reporting such adverse events. For example, when participants reported recent experiences of negative stress events, their performance on cognitive tasks requiring attention was more likely to be subpar than days without stress. This is also supported by research from Aggarwal et al. (2014), who found that higher baseline perceived stress was linked to cognitive decline over a six-year period. Moreover, this decline in performance was more noticeable among older adults than their younger counterparts.

Perceived stress influences how people react to distractions. When someone is already stressed, they may be more sensitive to distractions and find them more disturbing than when they are not. Stress reflects interactions between individuals and their environment, which they assess as threatening or taxing their resources in such a way that it will affect their cognitive performance (Owens et al., 2012; Storbeck, 2012; Luck & Vogel, 2013; Sliwinski et al., 2006). This cognitive interference not only affects immediate task performance but can also have lasting implications for overall well-being (Lazarus & Folkman, 1984). Therefore, understanding the intricate relationship between perceived stress, distraction, and cognitive function is crucial in elucidating how stressors can disrupt cognitive processes and impact individuals' well-being.

In addition, in terms of subjective age vs. chronological age, subjective age also predicts important aspects of well-being beyond chronological age, as mentioned by Hughes and Touron (2021). This might suggest that one important factor affecting how people experience and react to stress is their subjective age. Previous research (Shrira et al., 2014; Keyes et al., 2012) has shown that people with younger subjective ages typically have better mental health. In particular, younger subjective age was linked to lower levels of stress (Kotter-Grühn et al., 2015) and depressive symptoms (Keyes et al., 2012), suggesting that one's subjective age can serve as a critical factor influencing how one perceives, reacts to, and manages stressors in one's daily life.

In summary, our study contributes to the developing understanding of the complex dynamics between generational categories, perceived stress, subjective age, and distraction costs, highlighting the continuing influence of technology on cognitive performance across generations and emphasizing the multifaceted nature of stress responses in our increasingly digital world. Further research in this domain is warranted to deepen our insights into these intricate relationships and their implications for cognitive performance and well-being.

CONCLUSION AND FUTURE DIRECTION

The uneven distribution across generational groups is a notable limitation of our study. This disparity might introduce bias or limit the applicability of our results. Future research should strive for equal distribution of group sizes to ensure reliable comparisons and a deeper comprehension of the connections between generational categories, perceived stress, and distraction costs. Additionally, while we concentrated on distraction costs in the context of technology engagement, other potential confounding variables or factors might not have been fully considered, impacting how our results are interpreted. Furthermore, our study relies on cross-sectional data and does not include longitudinal data. Incorporating longitudinal research could provide insights into how these relationships between generational categories, perceived stress, and distraction costs evolve over time. Longitudinal studies would allow for a more in-depth exploration of potential causal relationships and how they may change as individuals age and experience different life circumstances.

For future research, it would be valuable to expand the scope of this study by measuring the impact of generational categories and perceived stress on distraction costs across multiple cognitive constructs, not limited to processing speed. This broader examination would provide a more comprehensive understanding of how these factors influence various aspects of cognitive performance. Additionally, conducting similar investigations across different cohorts and age groups could help identify potential trends and variations in the relationship between generational categories, perceived stress, and cognitive functioning. This comparative approach will show whether the observed effects are consistent across different generations or vary based on cohort-specific experiences and technological advancements.

CONFLICT OF INTEREST

The authors declared no potential conflicts of interest regarding the research, authorship, and/or publication of this article.

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