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When digital technology distracts: Impact on cognitive load and work productivity in Generation Z

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ABSTRACT

This study examines how digital technology distraction affects employees' cognitive load and work productivity, focusing on Generation Z employees at Telkom Indonesia Company within a hybrid work setting. Grounded in cognitive load theory, the research evaluates whether frequent notifications, multitasking, and overlapping digital activities heighten cognitive strain and reduce performance. Using a quantitative approach, data were collected from 108 respondents via online surveys, and purposive sampling was used to ensure a representative sample. The proposed model was analyzed using SmartPLS for the structural equation model with partial least squares, and process model 5 was applied to test mediation effects using SPSS. The findings show that digital technology distraction significantly increases cognitive load, and higher cognitive load subsequently decreases work productivity. In addition, digital technology distraction also has a significant direct adverse effect on work productivity. Mediation results indicate partial mediation, confirming that cognitive load is a central mechanism through which digital distractions translate into productivity loss. The study advances workplace digital-distraction literature by validating cognitive load theory in a real-world hybrid work environment and by providing evidence specific to Generation Z employees, who face high digital exposure at work. In practice, the findings highlight the need for digital exposure management and attention regulation strategies to sustain Generation Z performance in hybrid workplaces.

1. Introduction

Over the past two decades, rapid advances in digital technology have fundamentally transformed how modern organizations operate, particularly within highly connected hybrid work systems. Contemporary work environments are characterized by the simultaneous use of multiple digital communication platforms, including instant messaging, collaborative dashboards, and video conferencing, which create patterns of high connectivity and frequent interruptions (Ahmed et al., 2024; Godard & Holtzman, 2024; Sala et al., 2024). The global literature on digital workplaces indicates that hyperconnectivity and "always-on" expectations have become dominant job demands, increasing mental strain, and reducing employee well-being (Tarafdar et al., 2015; Kumar, 2024; Nastjuk et al., 2024).

Recent cross-national empirical studies further confirm that continuous exposure to notifications and parallel digital communication significantly increases cognitive fatigue and disrupts work focus in hybrid settings (Shaleha & Roque, 2024; Ash & Karmakar, 2025). Within the national context, Indonesia's organizational digital transformation has accelerated the adoption of platform-based work systems, especially in the telecommunications and technology sectors. Studies on the Generation Z workforce show susceptibility to digital distractions and multitasking, which negatively impact work focus (Cetindamar et al., 2021; Zheng et al., 2024; Kabakus et al., 2025; Yaseen et al., 2025). International research emphasizes that technology overload, digital multitasking, and notification-based interruptions are negatively associated with task performance and self-regulation (Anand et al., 2025; Kassa, 2025).

However, empirical studies that explicitly map the cognitive mechanisms underlying digital distraction within Indonesian organizations remain limited. Most prior research focuses on educational settings or on general internet use behavior. At the same time, organizational studies tend to examine technostress, cognitive load, and productivity as separate outcomes without testing their mediating relationships. Organizational evidence shows that repeated digital interruptions disrupt attentional regulation and slow task completion (Mark et al., 2008). Digital distraction is also experienced unevenly across generational cohorts in the workforce. Generation Z employees who grew up immersed in digital ecosystems are often characterized as digital natives with high technology dependence and strong expectations for digitalized work processes (Goryunova & Jenkins, 2023; Mandal et al., 2025).

Recent literature highlights a digital literacy paradox: Sustained exposure to multi-stream digital stimuli may heighten vulnerability to distraction, attention fragmentation, and rapid task switching. Cross organizational and behavioral studies indicate that individuals from Generation Z who are highly engaged with digital platforms tend to experience stronger tendencies toward continuous online monitoring and fear of missing out, which can intensify digital engagement and contribute to fatigue from constant connectivity (Çetinkaya et al., 2021). From a theoretical perspective, cognitive load theory posits that task performance deteriorates when information-processing demands exceed the capacity of working memory (Sweller et al., 2011). Experimental evidence further shows that multitasking and frequent digital interruptions increase cognitive load and reduce task efficiency and accuracy (Guo et al., 2015; Dehais et al., 2018; O'Keeffe et al., 2020).

Similar findings have also been reported in recent studies examining cognitive effort and performance in digital environments (Beyer et al., 2014; Poupard et al., 2025). This perspective is complemented by technostress theory, which posits that sustained information-technology pressures such as techno-overload and techno-invasion generate affective and cognitive strain that harms performance, particularly in remote and hybrid work arrangements (Di Dalmazi et al., 2022; Chang et al., 2024; Ioannou et al., 2024; Wu et al., 2024). Together, these frameworks suggest a clear causal pathway in which digital distraction elevates cognitive load, which subsequently diminishes work productivity. Although global attention to digital distraction is increasing, systematic empirical mapping within technology-intensive organizational contexts, especially in Indonesia, remains limited.

Previous studies generally confirm negative direct links between digital interruptions and performance, yet rarely test cognitive load as a mediator that explains how distraction translates into productivity loss, particularly among Generation Z employees in hybrid systems (Pratama et al., 2024). In this framework, Telkom Indonesia Company at Graha Merah Putih Bandung, Indonesia represents relevant research setting due to its

10.12928/fokus.v16i1.14769

advanced digital transformation and multi-platform workflow. Employees rely on systems such as MySofia, CRM, Webex, Microsoft Teams, and WhatsApp to manage both routine and strategic tasks. Research on organizational digital communication shows that dense notification streams and overlapping virtual meetings are associated with attention fragmentation and increased perceived mental load (Di Dalmazi et al., 2022; Lee et al., 2025).

Based on this background, the present study analyzes the relationships among digital technology distraction, cognitive load, and work productivity among Generation Z employees at Telkom Indonesia Company at Graha Merah Putih Bandung, Indonesia by testing the mediating role of cognitive load. By integrating cognitive load theory and technostress theory into a unified mediation model, this study clarifies the cognitive pathway linking digital work demands to productivity. It informs organizational digital governance strategies to protect cognitive resources and sustain employee performance in hybrid work environments.

2. Literature Review and Hypothesis Development

2.1. Literature Review

2.1.1. Conservation of Resources Theory

This study is grounded in the conservation of resources (COR) theory proposed by Hobfoll (1989). COR theory posits that individuals are motivated to obtain, retain, and protect valuable resources, including time, energy, attention, and cognitive capacity. Psychological strain occurs when these resources are threatened, lost, or insufficient to meet environmental demands. COR theory posits that individuals strive to protect and maintain valuable resources such as attention, energy, and cognitive capacity. In digitally intensive workplaces, continuous digital interruptions act as resource depleting demands that lead to strain and reduced performance outcomes (Halbesleben et al., 2014; Hobfoll et al., 2018).

Similarly, technology collaboration studies grounded in COR theory demonstrate that reductions in cognitive workload foster proactive behavior by reallocating resources to task-relevant processes (Liu et al., 2024). Within organizational settings, cognitive energy and attentional focus represent critical psychological resources that enable employees to perform effectively (Halbesleben et al., 2014; Magni et al., 2024). When external demands continuously consume these resources without adequate recovery, individuals experience resource depletion, leading to strain and reduced performance outcomes (Hobfoll et al., 2018).

In digitally intensive work environments, constant notifications, multitasking requirements, and platform overload function as resource-draining stressors. Repeated digital interruptions fragment attention and deplete cognitive resources, triggering processes that further deplete them (Leroy, 2009; Mark et al., 2016). According to COR theory, sustained resource loss results in diminished work effectiveness and productivity (Hobfoll et al., 2018). Thus, COR theory provides a macro-level explanatory framework for understanding how digital technology distraction reduces productivity through cognitive resource depletion mechanisms.

2.1.2. Digital Technology Distraction as a Resource-Depleting Demand

Digital technology distraction refers to interruptions and attentional shifts caused by digital devices, communication platforms, and online multitasking. In hybrid and digitally connected workplaces, employees are frequently exposed to overlapping streams of information, including emails, instant messaging, and collaborative platforms (Tarafdar et al., 2015; Mark et al., 2016). From a COR theory, these interruptions represent environmental demands that consume limited cognitive and attentional resources (Hobfoll et al., 2018). Each task switch requires mental reorientation, increasing cognitive strain and reducing sustained concentration (Rubinstein et al., 2001; Leroy, 2009). Over time, this continuous fragmentation of attention accelerates resource loss.

Therefore, digital technology distraction can be conceptualized as a chronic demand that depletes cognitive resources within organizational contexts. Digital technology distraction refers to the diversion of attention caused by technological stimuli such as notifications, parallel communications, pop-ups, and multitasking demands (Rosen et al., 2013; Mark et al., 2016). Within the framework of COR theory, these distractions can be conceptualized as environmental demands that consume valuable cognitive resources, particularly attention, working memory capacity, and psychological energy (Hobfoll et al., 2018). In contemporary digital and hybrid workplaces, such distractions are embedded in daily workflows and increasingly function as chronic digital job demands that require continuous cognitive regulation (Ayyagari et al., 2011; Tarafdar et al., 2015).

Prior studies also indicate that fear of missing out (FOMO) and intensive social media engagement increase problematic digital behavior and technology dependence among university students (Przybylski et al., 2013; Çetinkaya et al., 2021). Recent workplace research indicates that hyperconnectivity, technology overload, and always-on expectations generate persistent interruptions that contribute to strain and productivity loss (Tarafdar et al., 2015; Yu et al., 2023; Nastjuk et al., 2024).

From a COR theory, these conditions initiate resource-loss cycles, as employees must repeatedly allocate attentional resources to manage incoming stimuli while maintaining task performance (Hobfoll et al., 2018). Over time, this continuous reinvestment accelerates cognitive depletion (Halbesleben et al., 2014). The cognitive cost of these interruptions can also be explained through attention residue theory (Leroy, 2009), which proposes that traces of a previous task remain cognitively active after a task switch and interfere with subsequent performance (Leroy, 2009). Empirical organizational studies confirm that digital interruptions increase refocusing time and perceived strain, thereby reducing effective performance and work quality (Bailey & Konstan, 2006; Mark et al., 2016; Ash & Karmakar, 2025). Within the COR framework, attention residue represents incomplete resource recovery, further intensifying resource loss (Hobfoll et al., 2018).

Broader frameworks in digital workplace research identify technological hyperconnectivity and digital overload as demands associated with cognitive depletion, technostress, and impaired outcomes, particularly in hybrid work arrangements (Tarafdar et al., 2015; Nastjuk et al., 2024). These findings reinforce the argument that digital technology distraction operates as a resource-draining condition that undermines sustained task engagement (Mark et al., 2016). However, COR theory also emphasizes that resource availability can buffer loss processes (Hobfoll, 1989). Distracting digital inputs are not inherently detrimental when supported by adequate personal and organizational resources. Autonomy, digital self-efficacy and structured notification management may help employees conserve cognitive resources and mitigate the adverse effects of digital interruptions (Ioannou et al., 2024). Consistent with the job demands-resources (JD-R) model, such resources weaken the relationship between digital demands and cognitive strain, thereby reducing the likelihood of productivity impairment (Bakker & Demerouti, 2007).

10.12928/fokus.v16i1.14769

2.1.3. Cognitive Load as a Manifestation of Resource Depletion

To operationalize resource depletion at the psychological level, this study adopts the concept of cognitive load. Cognitive load reflects the mental effort required to process information and manage task demands (Sweller et al., 2011). While cognitive load is commonly explained through cognitive load theory, in this study, it is positioned within COR theory as an indicator of cognitive resource exhaustion (Paas & Sweller, 2012). When digital interruptions accumulate, employees must repeatedly reallocate attention and working memory capacity, increasing mental workload and perceived strain (Leroy, 2009; Mark et al., 2016).

Thus, cognitive load represents the psychological mechanism through which digital distraction translates into resource depletion (Hobfoll et al., 2018). The persistent engagement with digital technologies can lead to technostress and cognitive fatigue, which have been shown to affect productivity and mental well-being in organizational settings negatively (Tarafdar et al., 2015). Cognitive load reflects the mental effort required to process information and execute tasks effectively (Sweller et al., 2011). Within the framework of COR theory, cognitive load can be conceptualized as a manifestation of cognitive resource depletion. COR theory posits that individuals strive to preserve valuable resources such as attention, energy, and working memory capacity. When environmental demands continuously consume these limited cognitive resources, individuals experience strain that impairs task performance.

To explain the cognitive mechanism underlying this depletion process, this study draws on cognitive load theory, which posits that working memory has limited capacity and that performance deteriorates when information-processing demands exceed this capacity (Sweller, 1988; Sweller et al., 2011; Paas & Sweller, 2012). In digital work environments, repeated notifications, rapid task switching, and parallel digital activities increase extraneous cognitive load because employees must repeatedly reorient attention and reconstruct task context following interruptions. Empirical research shows that frequent task switching elevates cognitive load and reduces task efficiency and accuracy (Rubinstein et al., 2001; Mark et al., 2016; Poupard et al., 2025).

Studies in neuroscience and behavioral research also indicate that excessive digital engagement can impair cognitive control mechanisms and attentional regulation (Ophir et al., 2009; Liu et al., 2024; Méndez et al., 2024). In hybrid, technology intensive work arrangements, heightened demands for information and communication technology (ICT) and constant connectivity further accelerate resource consumption, leading to cognitive fatigue (Tarafdar et al., 2015). This pattern is consistent with findings on technostress linking digital overload to cognitive strain (Yu et al., 2023). From a COR theory, these recurring attentional shifts constitute cycles of resource reinvestment that gradually deplete available cognitive capacity.

Within this integrated theoretical perspective, cognitive load operates as a mediating mechanism that translates digital job demands into impaired task execution (Sweller et al., 2011). Digital technology distraction initiates resource loss, cognitive load reflects the depletion of attentional resources, and diminished productivity emerges as the performance consequence of sustained resource exhaustion (Yu et al., 2023). Nevertheless, COR theory also acknowledges that resource availability can buffer loss processes (Hobfoll, 1989). Employees with intense attention-control routines, high digital self-efficacy, or supportive work environments that minimize irrelevant alerts may conserve cognitive resources more effectively (Magni et al., 2024). In line with the JD-R model, these personal and organizational resources can buffer the pathway from digital demands to cognitive strain, thereby reducing the negative impact of distraction on performance outcomes (Bakker & Demerouti, 2007).

2.1.4. Work Productivity as a Resource-Based Outcome

Work productivity reflects the efficiency and effectiveness with which employees convert effort into task outcomes (Tangen, 2005). According to COR theory, performance declines when individuals lack sufficient cognitive and energetic resources to meet task demands (Hobfoll et al., 2018). In digitally saturated environments, productivity is particularly sensitive to attentional fragmentation (Mark et al., 2016). As cognitive resources are depleted, employees experience slower task completion, reduced accuracy, and diminished performance sustainability (Bailey & Konstan, 2006).

Therefore, work productivity can be understood as a downstream outcome of resource availability. Work productivity refers to employees' efficiency and quality in transforming inputs such as time, energy, and skills into valuable outputs (Sedarmayanti, 2017). Within the framework of COR theory, productivity can be conceptualized as an outcome of resource availability. COR theory posits that individuals strive to obtain, retain, and protect valuable resources, including cognitive capacity, attentional focus, and psychological energy. When these resources are preserved, employees can sustain task engagement and achieve optimal performance. Conversely, when resources are depleted, performance effectiveness declines.

In highly digitalized workplaces, productivity increasingly depends on sustained attention and the effective allocation of cognitive resources (Mark et al., 2016; Elshaer et al., 2024). Continuous exposure to digital job demands, such as notifications, multitasking requirements, and coordination pressures, represents a resource-draining condition (Tarafdar et al., 2015; Yu et al., 2023; Al Naqbi et al., 2024). These technology-related pressures are often conceptualized as technostress, which arises when individuals struggle to cope with the demands associated with information and communication technologies (Ayyagari et al., 2011). Empirical research further indicates that digital job demands and technostress are associated with reduced productivity under conditions of constant connectivity (Ayyagari et al., 2011; Yu et al., 2023).

From a COR theory, these demands accelerate resource loss cycles. Interruption-cost research further demonstrates that repeated disruptions fragment workflow into short resumption cycles, prolong task completion time, and increase error rates due to the cognitive effort required to reorient attention after each interruption (Bailey & Konstan, 2006; Leroy, 2009; Mark et al., 2016). Recent studies suggest that artificial intelligence and digital automation can influence productivity outcomes by reshaping cognitive effort allocation and task management processes (Stadler et al., 2024; Huang & Gursoy, 2024; Lee et al., 2025).

Other studies further indicate that digital technologies and artificial intelegence assisted systems can alter work processes and decision-making dynamics, thereby affecting performance and productivity outcomes (Almassaad et al., 2024; Verma & Chatterji, 2024; Zhou et al., 2024). Each interruption requires employees to reinvest cognitive resources to reconstruct the task context, thereby intensifying resource depletion. Thus, within the COR theory, reduced work productivity in digital environments can be understood as a consequence of

10.12928/fokus.v16i1.14769

accumulated resource loss. When attentional and cognitive resources are repeatedly consumed without sufficient recovery, employees experience diminished efficiency and lower performance outcomes.

2.1.5. Previous Studies

Building upon the COR theory, recent research increasingly conceptualizes digital workplace phenomena as resource-based processes. COR theory posits that individuals strive to obtain, retain, and protect valuable resources, and that strain occurs when these resources are threatened or depleted (Hobfoll, 1989; Halbesleben et al., 2014). Within digitally intensive environments, constant connectivity, multitasking demands, and technological interruptions function as chronic resource-draining conditions (Rosen et al., 2013; Nastjuk et al., 2024; Ioannou et al., 2024).

Integrating COR with cognitive load theory provides a multilevel explanation of how digital distraction translates into productivity loss. From a COR theory, digital technology distraction represents a job demand that consumes attentional and cognitive resources (Hobfoll, 1989; Halbesleben et al., 2014). Cognitive load theory specifies the micro-level mechanism: as working-memory capacity is limited, repeated task switching and information overload increase extraneous cognitive load (Rubinstein et al., 2001; Poupard et al., 2025). Elevated cognitive load signals cognitive resource depletion, reducing the capacity available for primary task execution and ultimately impairing work productivity (Pratama et al., 2024).

Empirical evidence supports this resource-depletion pathway. Recent technostress research demonstrates that ICT demands undermine performance primarily through cognitive and psychological strain mechanisms (Nastjuk et al., 2024; Ioannou et al., 2024). Similarly, digital overload and hyperconnectivity have been linked to attentional fragmentation, mental fatigue, and reduced task efficiency (Ophir et al., 2009; Rosen et al., 2013). Within the COR framework, these findings reflect resource-loss cycles in which repeated interruptions require continuous reinvestment of cognitive energy, accelerating depletion and diminishing performance (Halbesleben et al., 2014).

While the JD-R model complements this explanation by distinguishing between job demands and job resources, COR theory provides the broader motivational foundation explaining why sustained digital demands produce strain and performance decline (Hobfoll, 1989). Digital distraction can therefore be understood as a resource-draining demand, cognitive load as the manifestation of resource exhaustion, and productivity loss as the behavioral consequence of accumulated resource depletion (Halbesleben et al., 2014; Pratama et al., 2024).

This integrated resource-based model addresses a limitation in prior literature, which has often examined digital distraction, technostress, or productivity in isolation. By explicitly linking environmental demands, cognitive depletion mechanisms, and performance outcomes within a unified theoretical structure grounded in COR theory, the model offers a systematic explanation of how digital work environments influence productivity (Nastjuk et al., 2024; Pratama et al., 2024).

The framework is particularly relevant for Generation Z employees operating in hybrid, technology-intensive environments. As digital natives, Generation Z workers experience high levels of digital exposure (Prensky, 2001; Goryunova & Jenkins, 2023). However, recent generational research highlights a digital-literacy paradox in which technological fluency coexists with increased susceptibility to rapid switching and digitally induced depletion (Ophir et al., 2009; Goryunova & Jenkins, 2023). From a COR perspective, high digital exposure may accelerate resource consumption despite technological competence, making the distraction–cognitive load-productivity pathway especially pronounced among Generation Z employees (Przybylski et al., 2013; Nastjuk et al., 2024).

2.2. Hypothesis Development

2.2.1. Integrated Theoretical Mechanism

This study is grounded in COR theory, which posits that individuals strive to acquire, protect, and maintain valuable resources, including time, energy, attention, and cognitive capacity (Hobfoll et al., 2018). Performance deterioration occurs when environmental demands initiate a resource loss process that exceeds replenishment capacity (Halbesleben et al., 2014). Importantly, COR explains not only isolated stress reactions but also cumulative "loss spirals," where repeated resource depletion amplifies strain and undermines performance over time (Hobfoll et al., 2018). In digitally intensive workplaces, technology-mediated interruptions (notifications, instant messaging, parallel platforms, multitasking requirements) represent chronic job demands (Tarafdar et al., 2015; Mark et al., 2016). Each interruption requires cognitive disengagement, reorientation, and reconstruction of the task context (Leroy, 2009). From a COR theory, these repeated shifts consume attentional resources and trigger progressive depletion (Halbesleben et al., 2014).

To specify the micro-level mechanism of this depletion, cognitive load theory explains that working memory has limited capacity, and excessive information-processing demands increase extraneous cognitive load (Sweller, 1988; Sweller et al., 2011; Paas & Sweller, 2012). Thus, digital technology distraction can be conceptualized as an external demand that initiates a resource loss process, which manifests psychologically as cognitive load and behaviorally as reduced productivity (Tarafdar et al., 2015). Accordingly, this study proposes a sequential resource depletion mechanism: Digital technology distraction → Cognitive resource depletion (Cognitive load) → Reduced work productivity. This framing ensures that each hypothesis is embedded within a coherent macro–micro theoretical system rather than treated as an isolated bivariate association.

2.2.2. Positive Effect of Digital Technology Distraction on Cognitive Load

COR theory argues that repeated exposure to demanding stimuli accelerates resource loss (Hobfoll et al., 2018). Digital interruptions require continuous attentional switching, which consumes executive control resources and diminishes cognitive reserves (Rubinstein et al., 2001; Leroy, 2009). The reinvestment of attention after each interruption imposes cognitive restart costs (Bailey & Konstan, 2006). Cognitive load theory further explains that such task switching increases extraneous cognitive load because employees must process irrelevant or secondary stimuli alongside primary task demands (Sweller, 1988; Sweller et al., 2011; Paas & Sweller, 2012). Empirical evidence in hybrid and ICT-intensive environments shows that digital overload and hyperconnectivity significantly predict momentary cognitive overload, mental fatigue, and attentional fragmentation (Tarafdar et al., 2015; Yu et al., 2023). Studies on digital multitasking also demonstrate that frequent switching increases perceived cognitive strain and working-memory burden (Ophir et al., 2009). Synthesizing COR and cognitive load theory indicates that digital technology distraction acts as a persistent resource-draining demand whose psychological manifestation is elevated cognitive load (Halbesleben et al., 2014). **H_1: Digital Technology Distraction Has a Positive Effect on Cognitive Load**

10.12928/fokus.v16i1.14769

2.2.3. Negative Effect of Digital Technology Distraction on Work Productivity

Beyond indirect cognitive mechanisms, COR theory predicts that sustained resource loss directly impairs performance outcomes (Hobfoll et al., 2018). When attentional and cognitive resources are fragmented, employees have fewer resources available for deep work and sustained execution (Mark et al., 2016). Interruption-cost research demonstrates that digital disruptions increase task completion time, error rates, and workflow instability (Bailey & Konstan, 2006; Mark et al., 2016). Recent organizational studies confirm that ICT-driven interruptions and notification density significantly reduce performance stability and output quality in digital work environments (Ayyagari et al., 2011; Tarafdar et al., 2015). From a COR perspective, digital technology distraction represents a chronic demand that directly undermines productivity by immediately fragmenting cognitive resources, even before cumulative strain effects emerge (Hobfoll et al., 2018). **H_2: Digital Technology Distraction Has a Negative Effect on Work Productivity**

2.2.4. Negative Effect of Cognitive Load on Work Productivity

Within the COR framework, cognitive load reflects the internal manifestation of resource depletion (Hobfoll et al., 2018). When working memory is overloaded, individuals experience reduced attentional endurance, slower information processing, and diminished task accuracy (Sweller et al., 2011). Cognitive load theory predicts that performance deteriorates when cognitive demands exceed capacity limits (Sweller, 1988; Sweller et al., 2011; Paas & Sweller, 2012). Contemporary research on digital multitasking contexts confirms that elevated extraneous cognitive load reduces efficiency and increases the likelihood of errors. Technostress research further demonstrates that cognitive strain mediates performance declines in technology-intensive workplaces (Ayyagari et al., 2011; Tarafdar et al., 2015). Therefore, excessive cognitive load diminishes the mental resources necessary for productive execution. **H_3: Cognitive Load Has a Negative Effect on Work Productivity**

2.2.5. The Effect of Digital Technology Distraction on Work Productivity through Cognitive Load

COR theory emphasizes that environmental demands initiate loss spirals in which initial resource depletion triggers psychological strain and subsequent performance deterioration (Hobfoll et al., 2018). Within this framework, digital technology distraction represents the initiating demand, cognitive load represents the internal strain mechanism, and reduced productivity represents the performance consequence (Halbesleben et al., 2014). Recent technostress studies provide empirical support for mediated pathways, showing that ICT demands impair performance primarily through cognitive and psychological strain mechanisms (Tarafdar et al., 2015; Yu et al., 2023). Thus, the model predicts a sequential mechanism rather than a simple direct association. **H_4: Cognitive Load Mediates the Effect of Digital Technology Distraction on Work Productivity**

2.3. Research Framework

Figure 1 presents four hypotheses consistent with the proposed model. Digital technology distraction directly increases cognitive load and directly decreases work productivity. Cognitive load also directly decreases work productivity, and simultaneously mediates the effect of digital technology distraction on work productivity, forming a partial mediation structure.

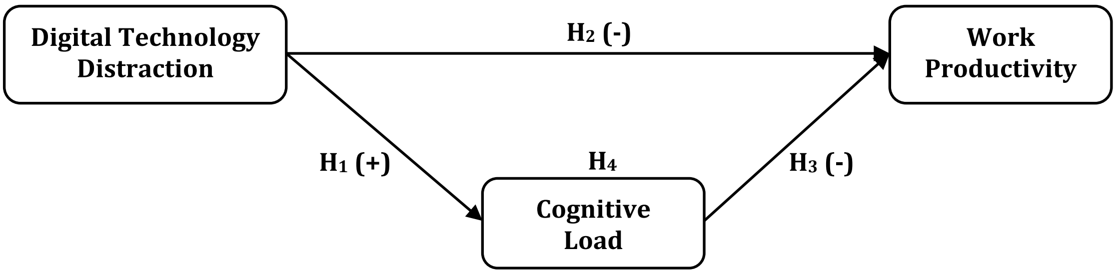

Figure 1. Research Framework

3. Research Methods

3.1. Population and Sampling Method

This study applied an explanatory quantitative design to test the causal relationships among digital technology distraction, cognitive load, and work productivity. An explanatory approach is appropriate because the research aims to verify directional effects and mediation within a theoretically specified model. The study was conducted at Telkom Indonesia Company at Graha Merah Putih Bandung, Indonesia, a technology-intensive organization with a hybrid work system and multi-platform digital workflows. This context is relevant because recent digital workplace literature indicates that hyperconnectivity, digital overload, and always-on communication demands are increasingly salient job demands that can shape cognitive strain and performance in hybrid settings.

The population consisted of 150 Generation Z employees (born 1997–2012) working across operations, customer handling, finance, human capital, and information technology (IT) services. Generation Z was chosen as the target cohort because contemporary generational studies highlight their high digital intensity and the digital-literacy paradox, in which strong digital fluency can coexist with greater susceptibility to distraction and cognitive depletion in always-connected workplaces. This makes Generation Z theoretically relevant for examining the distraction–load–productivity mechanism.

Sample size was determined using the Isaac and Michael (1995) formula with a 5% error rate, yielding a minimum sample size of 108 respondents. Purposive sampling was used to ensure respondents met the inclusion criteria: Generation Z employees, tenure of at least one year, and daily active use of three or more digital applications. These criteria ensured participants had stable exposure to digital workplace demands and sufficient familiarity with organizational digital tools.

3.2. Data Collecting Method

Primary data were collected via a structured online questionnaire distributed via Google Forms from April to May 2025. Ethical standards were upheld through informed consent, anonymity, and voluntary participation. To reduce common method bias procedurally, respondents were assured of confidentiality, informed that there were no right or wrong answers, and items were randomized to minimize response patterning and evaluation apprehension.

Three constructs were measured using established instruments adapted to the workplace context and rated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Digital technology distraction (DTD) was measured using items adapted

 10.12928/fokus.v16i1.14769

from validated workplace technology interruption and distraction scales that capture notification overload, parallel communications, and multitasking demands recent digital workplace distraction measures (Rosen et al., 2013; Mark et al., 2016). The construct consisted of approximately nine items, including perceptions of frequent interruptions from digital notifications and the tendency to switch between multiple applications during task completion.

Cognitive load (CL) was measured through a subjective mental-effort rating approach grounded in cognitive load theory, which has been widely validated for capturing perceived cognitive strain in applied settings (Paas & Sweller, 2012). This construct included about nine items reflecting perceived mental effort and overload while handling digital work demands. Work productivity (WP) was assessed using self-reported productivity and efficiency measures commonly applied in organizational research, focusing on task completion quality, efficiency, and continuity productivity self-report approaches in digital work studies (Koopmans et al., 2013). The scale comprised around eight items evaluating perceived efficiency and work output quality in digitally mediated work routines. All instruments were translated and back-translated to ensure semantic equivalence, and a small pilot test was conducted to confirm the clarity and contextual suitability of items before complete data collection.

3.3. Data Analysis Method

Data analysis followed a two-stage strategy. First, partial least squares structural equation modeling (PLS-SEM) was conducted using SmartPLS 5.0 to evaluate measurement adequacy and test structural relationships, including path coefficients, R^2 values, and bootstrapped indirect effects. PLS-SEM is appropriate for predictive causal modeling with latent variables and mediation analysis, and recommended procedures were followed (Hair & Alamer, 2022). Measurement evaluation confirmed acceptable convergent validity (outer loadings value above 0.6), internal consistency (Cronbach's alpha above 0.6, composite reliability above 0.7).

Second, PROCESS macro model 5 was employed as a robustness check for mediation, providing regression-based estimates of direct and indirect effects with bias-corrected bootstrapped confidence intervals (Hayes, 2018). The PROCESS analysis was executed in IBM SPSS Statistics 28 with 5.000 bootstrap samples and a 95 percent confidence interval ($p < 0.05$). Using both PLS-SEM and PROCESS is justified because PLS-SEM ensures valid latent-construct modeling and overall structural verification. At the same time, PROCESS offers a widely recognized confirmatory test of mediation strength and consistency.

4. Results and Discussion

4.1. Descriptive Analysis

Table 1 presents respondent characteristics. Most respondents are male (64.8%) and concentrated in the 27–28 age group (41.7%), reflecting early-career knowledge workers. In terms of division, many respondents work in Information Technology (17.3%), network operations (16%), and customer handling (14.7%), which are highly digitalized functions requiring continuous platform interaction. Regarding tenure, 86.1% have worked more than one year, suggesting stable exposure to Telkom's digital workflow and adequate adaptation to its platform ecosystem. Overall, this demographic profile supports the suitability of the sample for examining distraction-related cognitive strain and productivity outcomes in a hybrid, technology-intensive setting.

Regarding tenure, the majority of employees (86.1%) have worked for more than 1 year, indicating they are relatively stable and well-adapted to the company's digital work environment. In terms of monthly income, most respondents (85.2%) earn between IDR 5.000.001 and IDR 10.000.000, while 14.8% earn between IDR 10.000.001 and IDR 15.000.000. No respondents earn below IDR 5.000.000 or above IDR 15.000.000, which aligns with their early career status as Generation Z employees. Overall, this demographic profile indicates that the participants are digitally skilled and adaptive, and predominantly in operational and IT-based roles, aligning with the purpose of this study, which examines how digital technology distractions affect cognitive load and productivity.

Table 1. Characteristics of Respondents

Model	Characteristics	Frequency (N)	Percentage (%)
Gender	Male	70	64.8%
	Female	38	35.2%
Age	22-24 years old	28	25.9%
	25-26 years old	35	32.4%
	27-28 years old	45	41.7%
Division	Human Capital & General Affairs	10	9.3%
	Finance & Accounting	9	8%
	Information Technology	19	17.3%
	Compliance & Risk Management	6	6%
	Corporate Affairs & Communication	8	7.3%
	Strategic Planning & Investment	8	7.3%
	Internal Audit	5	4.7%
	Network Operations	17	16%
	Customer Handling (Experience & Care)	16	14.7%
	Enterprise Sales & Service	10	9.3%
Work Tenure	< 1 year	15	13.9%
	1-3 years	45	41.7%
	4-6 years	48	44%
Income	IDR 5.000.001 – IDR 10.000.000	92	85.2%
	IDR 10.000.001 – IDR 15.000.000	16	14.8%

4.2. Validity Test

The Table 2 show that all questionnaire items measuring the independent variables digital technology distraction (DTD), cognitive load (CL), and work productivity (WP) met the validity criteria, as the outer loadings value above 0.6. This indicates that all items possess adequate construct validity and are suitable for further analysis.

Table 2. Validity Test Results

Item Indicator	Digital Technology Distraction	Cognitive Load	Work Productivity
DTD1	0.673		
DTD2	0.670		
DTD3	0.663		
DTD4	0. 681		
DTD5	0.709		
DTD6	0.693		
DTD7	0.653		
DTD8	0.650		
DTD9	0.714		
CL1		0.706	
CL2		0.741	

10.12928/fokus.v16i1.14769

Item Indicator	Digital Technology Distraction	Cognitive Load	Work Productivity
CL3		0.730	
CL4		0.677	
CL5		0.692	
CL6		0.711	
CL7		0.711	
CL8		0.661	
CL9		0.686	
WP1			0.654
WP2			0.712
WP3			0.643
WP4			0.724
WP5			0.654
WP6			0.638
WP7			0,679
WP8			0.731

4.3. Reliability Test

Reliability refers to the consistency of respondents' answers when the instrument is administered repeatedly. The reliability test was conducted to ensure that the questionnaire measuring digital technology distraction, cognitive workload, and work productivity produced dependable and stable results. The Table 3 demonstrate that all three variables are reliable, as their Cronbach's alpha values exceed the minimum acceptable threshold of 0.6 and the composite reliability value above 0.7. These values indicate a high level of internal consistency, confirming that the research instrument is appropriate for use in subsequent statistical analyses.

Table 3. Reliability Test Result

Variable	Cronbach's Alpha	Composite Reliability
Digital Technology Distraction	0.924	0.940
Cognitive Load	0.918	0.936
Work Productivity	0.911	0.931

4.4. Hypothesis Test

Table 4 show all proposed hypothesis are statistically supported at the 95% confidence level, as evidenced by their respective p-values. First hypothesis show digital technology distraction has a positive effect on cognitive load. This result suggests that frequent exposure to notifications, multitasking, and switching between applications significantly elevates employees' cognitive strain. Second hypothesis show digital technology distraction has a negative effect on work productivity. The negative coefficient indicates that higher levels of digital distraction significantly reduce focus, response accuracy, and task efficiency.

Third hypothesis show cognitive load has a negative effect on work productivity. This finding indicates that excessive mental effort significantly diminishes performance efficiency. Last, the fourth hypothesis show the indirect effect of digital technology distraction on work productivity through cognitive load is also significant. The results indicate partial mediation, as both the direct effect and the indirect effect remain statistically significant. This suggests that digital technology distraction influences productivity both directly and indirectly through increased cognitive strain.

Table 4. Hypothesis Test Result

Hypothesis	Coefficient (B)	SE	t-value	p-value	95% CI (LLCI, ULCI)
Digital Technology Distraction → Cognitive Load	0.9406	0.046	20.36	0.000	[0.8490, 1.0322]
Digital Technology Distraction → Work Productivity	–0,4917	0.080	-6.140	0.000	[-0.6505, -0.3330]
Cognitive Load → Work Productivity	–0,3316	0.076	-4.360	0.000	[-0.4822, -0.1810]
Digital Technology Distraction → Cognitive Load → Work Productivity	–0,3120	0.076	-4.070	0.000	[-0.4766, -0.1766]

4.5. Discussion

4.5.1. The Effect of Digital Technology Distraction on Cognitive Load

The results show that digital technology distraction has a positive effect on cognitive load. This finding indicates that constant exposure to notifications, instant messaging, and overlapping digital tasks creates attentional fragmentation and increases mental processing demands (Leroy, 2009; Mark et al., 2016). From the perspective of digital distraction theory, frequent interruptions function as a form of digital job demand that continuously competes for limited cognitive resources (Tarafdar et al., 2015). Similar studies in hybrid and technology-intensive workplaces report that persistent ICT interruptions significantly elevate perceived cognitive strain and attentional fatigue (Ayyagari et al., 2011; Yu et al., 2023). Therefore, the strong relationship observed in this study confirms that digital distraction is not a minor disturbance but a central factor shaping employees' cognitive workload.

4.5.3. The Effect of Digital Technology Distraction on Work Productivity

In addition to its indirect cognitive impact, digital technology distraction also shows a positive effect on work productivity. This suggests that interruptions disrupt workflow beyond cognitive depletion alone (Mark et al., 2016). Interruption-cost research explains that each digital switch requires refocusing time and creates restart overhead that accumulates into measurable productivity loss (Bailey & Konstan, 2006; Leroy, 2009; Mark et al., 2016). Recent studies on hybrid digital work further indicate that constant connectivity and responsiveness expectations intensify performance pressure and reduce output quality (Tarafdar et al., 2015; Yu et al., 2023). These findings align with the present results, confirming that digital distraction directly interferes with efficient task completion.

4.5.2. The Effect of Cognitive Load on Employee Work Productivity

The findings further demonstrate that cognitive load has a negative effect on employee work productivity. According to cognitive load theory, excessive extraneous load consumes working memory capacity required for sustained concentration, problem-solving, and accurate task execution (Sweller, 1988; Sweller et al., 2011; Paas & Sweller, 2012). When employees repeatedly switch tasks due to digital interruptions, cognitive resources are depleted, resulting in slower performance and increased error risk (Rubinstein et al., 2001). Empirical evidence from recent research similarly shows that ICT overload and multitasking demands reduce task efficiency and productivity in hybrid work environments (Tarafdar et al.,

10.12928/fokus.v16i1.14769

2015; Yu et al., 2023). Thus, the present study extends cognitive load theory to organizational settings by confirming that elevated cognitive load directly undermines workplace productivity.

4.5.4. The Effect of Digital Technology Distraction on Work Productivity through Cognitive Load

The mediation analysis confirms that cognitive load significantly mediates the relationship between digital technology distraction and work productivity, because the direct effect remains significant, the mediation is partial, indicating that distraction impairs productivity through multiple pathways. Beyond cognitive overload, productivity losses may also arise from emotional technostress reactions and coordination friction created by parallel communication streams (Rosen et al., 2013; Nastjuk et al., 2024). Prior technostress research supports the existence of such multi-path mechanisms, where cognitive and affective strain jointly reduce work performance (Ayyagari et al., 2011; Tarafdar et al., 2015; Ioannou et al., 2024). These results provide empirical evidence supporting the mediation hypothesis and confirm that cognitive load serves as a key explanatory mechanism linking distraction to productivity decline (Pratama et al., 2024).

4.6. Contextual and Practical Implications

This study offers novel insight into why the distraction–load relationship is powerful for Generation Z employees in a hybrid telecommunications context. Although Generation Z workers are digital natives, research highlights a digital-literacy paradox in which high technological fluency coexists with increased vulnerability to attentional depletion and digital fatigue (Prensky, 2001; Goryunova & Jenkins, 2023). Organizational norms emphasizing rapid responsiveness and constant connectivity may amplify notification pressure and multitasking demands (Tarafdar et al., 2015). Consequently, distraction becomes a potent cognitive stressor with measurable consequences for productivity.

From a practical perspective, the findings suggest targeted organizational interventions. Companies should reduce unnecessary switching demands through structured notification governance, asynchronous communication for non-urgent tasks, protected deep-work periods, and improved meeting coordination. Research on workplace productivity and technostress demonstrates that such interventions effectively lower cognitive strain and enhance sustained performance in hybrid environments (Ayyagari et al., 2011; Yu et al., 2023). Implementing these strategies can help organizations mitigate the adverse effects of digital distraction while supporting healthier and more productive work systems.

5. Conclusion

This study concludes that digital technology distraction significantly influences employees' cognitive processes and overall work productivity among Generation Z employees at Telkom Indonesia Company at Graha Merah Putih Bandung, Indonesia. Addressing the research objectives, the findings clarify that persistent exposure to notifications, multitasking, and overlapping communication demands substantially increases cognitive strain and weakens employees' capacity to maintain focus and task efficiency. Empirically, digital distraction strongly elevates cognitive load, while both distraction and cognitive load significantly reduce productivity. The significant indirect pathway further confirms that cognitive load is a central mechanism that translates distraction into productivity loss, reinforcing cognitive load theory (Sweller et al., 2011) and aligning with

Sedarmayanti's (2017) view of productivity as the effective and efficient use of time, energy, and skills. Together, these results show that digital distraction is not merely a behavioral inconvenience but a technologically driven cognitive depletion process that undermines sustainable performance in hybrid digital workplaces.

From a managerial perspective, the results imply specific and evidence-based interventions, because distraction affects productivity partly through cognitive load, organizations should prioritize policies that reduce extraneous cognitive demands and task switching. Concrete steps include tiered notification governance (urgent versus non-urgent alerts), shifting routine coordination to asynchronous channels, protecting uninterrupted deep work periods, and preventing meeting overlap, especially in platform-dense hybrid arrangements (Yu et al., 2023). Since the mediation pathway is significant, productivity improvement should also involve attention regulation programs such as digital mindfulness, task-batching routines, and focus-recovery training. These interventions directly target the strongest empirical mechanism identified in this study: Reducing distraction intensity lowers cognitive load, thereby restoring productive capacity.

Despite these contributions, several limitations constrain interpretation. First, the reliance on self-reported measures may inflate perceptual associations and cannot fully capture actual interruption behavior or real output performance; thus, effect sizes should be interpreted as perceived cognitive-behavioral links rather than purely objective causal magnitudes. Second, because the study was conducted within a single telecommunications organization and focused on Generation Z employees, generalization to other industries, organizational cultures, or older cohorts should be made cautiously, particularly in workplaces with different digital governance climates or lower communication interdependence. Third, the cross-sectional design limits temporal and causal inference; the model cannot observe whether distraction effects intensify, stabilize, or diminish as employees adapt over time. These boundary conditions suggest that the observed relationships may vary depending on alert relevance, digital self-efficacy, autonomy, and organizational notification norms.

Future research should therefore extend this work using more robust and innovative designs. Longitudinal or experience-sampling approaches could capture daily dynamics of distraction, cognitive fatigue, and performance fluctuations. Experimental or natural-experiment studies that manipulate notification rules or meeting structures would strengthen causal inference. In addition, objective digital-trace indicators, such as notification counts, application-switching frequency, or screen-time logs, complement self-reports and enhance validity. Testing moderators such as digital literacy, organizational support, autonomy, and task interdependence would clarify when distraction becomes most harmful or when resources buffer its effects (Bakker & Demerouti, 2007).

In summary, this research provides theoretical enrichment and practical implications by integrating digital distraction theory, cognitive load theory, and work productivity frameworks into a unified explanatory model relevant to hybrid digital work. Practically, it highlights the need for a deliberate balance between connectivity and cognitive sustainability, urging organizations to design digital ecosystems that are not only efficient but also attention-preserving. Sustained productivity in the digital era depends as much on managing cognitive load and attentional resources as on technological sophistication, and this principle should guide future workplace innovation.

10.12928/fokus.v16i1.14769

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