Research Article | ISSN: 3108-3021

Journal of CORTEXPLORE

Cognitive Offloading Collapse: Digital Dependency and the Restructuring of Attention and Reasoning in Generation Z

Reem Suju Michael [1] | D M Renuka Devi [2]

Abstract

The integration of digital technologies into everyday cognition has fundamentally altered how individuals process, store, and retrieve information. While cognitive offloading through digital devices enhances efficiency, its sustained and habitual use may reshape internal cognitive engagement. Despite growing interest in digital dependency, existing research remains fragmented, with limited understanding of the mechanisms linking externalized cognition to higher-order reasoning outcomes. Addressing this gap, the present study introduces the Cognitive Offloading Collapse (COC) framework, which conceptualizes a sequential pathway through which digital dependency influences analytical reasoning via cognitive offloading, attention fragmentation, and working memory engagement.

A cross-sectional survey was conducted with 415 Generation Z participants (aged 18–25 years), and the proposed model was tested using confirmatory factor analysis and structural equation modeling. The findings indicate that digital dependency is positively associated with cognitive offloading, which in turn contributes to increased attention fragmentation. Attention fragmentation was negatively related to working memory engagement, which subsequently predicted analytical reasoning performance. Mediation analysis suggests that cognitive offloading operates as a central mechanism, with a significant serial pathway linking digital dependency to reasoning outcomes.

Importantly, the results reflect moderate effect sizes, indicating patterns of cognitive restructuring rather than deterministic decline. The study contributes to emerging discussions on human–technology co-cognition by offering a theoretically integrated and empirically supported model of how digital environments influence cognitive processes. Practical implications are discussed for educational design, digital behavior regulation, and human–AI interaction in contemporary learning and work contexts

Keywords: Cognitive Offloading | Digital Dependency | Attention Fragmentation| Working Memory Engagement | Generation Z | Cognitive Restructuring | Human–AI Interaction

Submitted : April 16, 2026

Published : April 30, 2026

DOI: doi.org/10.65320/jce.vol.1.issue2.10

1* Jain University, Bengaluru, India. (reem.suju@yahoo.com)

2 Jain University, Bengaluru, India. (renuka097@gmail.com)

Corresponding Author

I. Introduction

The rapid integration of digital technologies into everyday life has fundamentally transformed how individuals engage with information, solve problems, and make decisions. Smartphones, search engines, cloud-based storage systems, and algorithmically curated platforms have become embedded in routine cognitive processes, enabling individuals to access and manipulate information with unprecedented ease. Within this evolving landscape, cognition is no longer confined to internal mental processes but is increasingly distributed across external digital systems. This shift has led to growing scholarly interest in cognitive offloading, defined as the delegation of cognitive tasks such as memory storage, information retrieval, and problem-solving to external tools and devices.

Recent evidence suggests that digital technologies are increasingly integrated into cognitive processes, influencing attention, memory, and decision-making patterns in complex ways (Firth et al., 2019; Parry et al., 2021). Contemporary research further highlights that interactions with AI-enabled systems are not merely tools for information access but may actively shape cognitive engagement and metacognitive awareness (Jose, 2025; Wang et al., 2024).

While cognitive offloading can enhance efficiency and reduce mental workload, its long-term implications for internal cognitive functioning remain insufficiently understood. Existing research suggests that individuals increasingly rely on digital devices to store information rather than encoding it internally, a phenomenon often described as “external memory reliance” or “digital amnesia.” At the same time, the proliferation of digital platforms particularly those driven by algorithmic content delivery has introduced new patterns of attentional engagement characterized by rapid task-switching, fragmented focus, and reduced sustained attention. These developments raise critical questions regarding the cumulative effects of digital dependency on core cognitive processes, including working memory and analytical reasoning.

Emerging studies have also differentiated between passive and active digital engagement, suggesting that the cognitive consequences of technology use are context-dependent rather than uniformly negative (Hauge Nustad & Abrahamsson, 2026). This reinforces the need to move beyond generalized measures such as screen time toward more nuanced constructs capturing how individuals interact with digital environments.

Despite a growing body of literature examining digital behavior and cognition, existing research remains fragmented, with limited integration of cognitive offloading, attentional processes, and higher-order reasoning within a unified explanatory framework (Montag & Elhai, 2020; Zhang et al., 2023). Much of the existing research has focused on isolated constructs such as screen time, multitasking, or social media use, often yielding mixed or context-dependent findings. For instance, some studies highlight the cognitive benefits of digital tools in enhancing access to information and supporting distributed problem-solving, while others point to potential drawbacks such as reduced attention span and diminished deep processing. However, relatively few studies have attempted to integrate these perspectives into a coherent explanatory framework that captures the mechanisms through which digital dependency may influence higher-order cognitive outcomes.

In particular, there is limited empirical work examining the sequential cognitive pathway linking digital dependency to analytical reasoning. Specifically, it remains unclear how habitual reliance on digital tools may lead to increased cognitive offloading, how such offloading may contribute to attentional fragmentation, and how these processes collectively influence working memory engagement and reasoning performance. Addressing this gap is essential for developing a more nuanced understanding of how contemporary digital environments shape cognition—not as a simple process of enhancement or decline, but as a complex reconfiguration of cognitive processes.

To address these limitations, the present study introduces the concept of Cognitive Offloading Collapse (COC). The COC framework conceptualizes a structured pathway in which sustained digital dependency is associated with increased reliance on external cognitive supports, which may reduce engagement in effortful internal processing. Over time, this pattern may contribute to fragmented attentional states and reduced activation of working memory resources, ultimately influencing analytical reasoning outcomes. Importantly, the term “collapse” is not used to imply a deterministic or irreversible decline, but rather to denote a potential reduction in internal cognitive engagement within specific contexts of high digital reliance.

The focus on Generation Z (Gen Z) is particularly relevant in this context. As the first cohort to grow up in fully digitized environments, Gen Z individuals have been continuously exposed to digital technologies during critical developmental stages. Their cognitive habits, therefore, are likely shaped by sustained interaction with digital systems, making them an appropriate population for examining the long-term implications of cognitive offloading. Understanding these patterns is essential not only for psychological theory but also for practical domains such as education, workforce readiness, and human–AI interaction design.

The present study aims to develop and empirically test a structural model that captures the relationships among digital dependency, cognitive offloading, attention fragmentation, working memory engagement, and analytical reasoning. By integrating insights from cognitive load theory, distributed cognition, and contemporary digital cognition research, the study seeks to contribute to a more comprehensive understanding of how digital environments influence cognitive functioning.

The contributions of this study are threefold. First, it advances theory by introducing the Cognitive Offloading Collapse framework, which integrates previously disconnected constructs into a unified model of digital cognition. Second, it provides empirical evidence using a

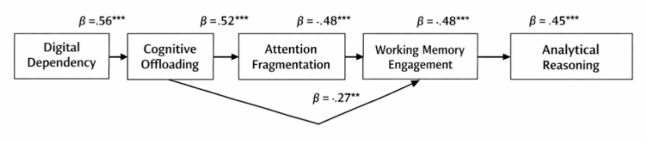
CORTEXPLORE | Journal of CORTEXPLORE

sample of Generation Z individuals and robust analytical techniques, including confirmatory factor analysis and structural equation modeling. Third, it offers practical insights for educators, policymakers, and organizations seeking to design environments that balance the benefits of digital tools with the need to sustain deep cognitive engagement.

In doing so, the study moves beyond binary narratives of cognitive enhancement versus decline and instead proposes a more nuanced perspective: that digital dependency may be associated with cognitive restructuring, wherein the balance between internal and external cognitive processes is altered. This perspective provides a foundation for future research aimed at understanding how individuals can effectively navigate and regulate cognition in increasingly digital environments.

To provide a structured representation of the proposed relationships, the conceptual model underlying the Cognitive Offloading Collapse (COC) framework is presented in Figure 1.

Figure 1. *Cognitive Offloading Collapse (COC) model*



This Conceptual model illustrating the Cognitive Offloading Collapse (COC) framework, depicting the relationships among digital dependency, cognitive offloading, attention fragmentation, working memory engagement, and analytical reasoning.

This study responds to this gap by offering a theoretically integrated and empirically validated framework that advances understanding of cognitive dynamics in digitally mediated environments.

II. Materials and Methods

2.1 Research Design

The present study employed a quantitative, cross-sectional research design to examine the relationships among digital dependency, cognitive offloading, attention fragmentation, working memory engagement, and analytical reasoning in Generation Z. A structural modeling approach was adopted to test the proposed Cognitive Offloading Collapse (COC) framework, allowing for the simultaneous estimation of multiple direct and indirect relationships among latent constructs.

Cross-sectional survey designs are widely used in digital cognition research to capture behavioral and perceptual patterns associated with technology use in naturalistic settings (Montag & Elhai, 2020). While such designs do not establish causality, they provide a robust basis for testing theoretically grounded structural relationships, particularly when supported by strong measurement models and appropriate statistical controls (Kline, 2016).

2.2 Participants and Procedure

The study sample comprised 415 respondents aged between 18 and 25 years, representing Generation Z. Participants were recruited using a stratified sampling approach across higher educational institutions to ensure diversity in academic background and digital usage patterns.

Data were collected using a structured questionnaire administered both online and offline. Prior to participation, respondents were informed about the purpose of the study, assured of confidentiality, and provided informed consent. Participation was voluntary, and no identifying information was collected.

The sample size of 415 was considered adequate for structural equation modeling, exceeding recommended thresholds for models with moderate complexity and ensuring stable parameter estimation (Hair et al., 2019). The ratio of sample size to estimated parameters was within acceptable limits, supporting the reliability of model estimation.

2.3 Measures

All constructs were measured using established and adapted scales from prior literature. Responses were recorded on a five-point Likert scale ranging from 1 (“Strongly Disagree”) to 5 (“Strongly Agree”).

Digital Dependency (DD)

Digital dependency was assessed using adapted items from problematic smartphone use and digital reliance scales, capturing the extent to which individuals depend on digital devices for daily cognitive tasks. Prior research has conceptualized digital dependency as a behavioral pattern characterized by habitual reliance on digital tools for information access and task execution (Elhai et al., 2017).
The scale consisted of 5 items (e.g., “I rely on my digital devices to remember important information” adapted from prior research, demonstrating acceptable reliability in previous studies (Elhai et al., 2017).

Cognitive Offloading (CO)

Cognitive offloading was measured using items reflecting the tendency to rely on external tools for memory and problem-solving tasks. This construct aligns with the broader literature on distributed cognition, where individuals externalize cognitive processes to reduce internal cognitive load (Risko & Gilbert, 2016). Recent work has also highlighted the growing relevance of digital offloading in everyday cognition (Jose, 2025).

The construct was measured using 4 items (e.g., “I prefer to store information on my phone rather than remembering it” consistent with cognitive offloading literature (Risko & Gilbert, 2016).

Attention Fragmentation (AF)
Attention fragmentation was assessed using adapted items from attention control and multitasking scales. This construct reflects the degree to which individuals experience interruptions, rapid task-switching, and difficulty sustaining attention. Research suggests that digital environments, particularly those driven by algorithmic content delivery, contribute to fragmented attentional patterns (Hauge Nustad & Abrahamsson, 2026). The scale consisted of 4 items (e.g., "I find it difficult to maintain focus on a single task without interruption" adapted from attention control literature (Cain et al., 2021).

Working Memory Engagement (WME)
Working memory engagement was measured using items assessing the extent to which individuals actively process and retain information during cognitive tasks. Working memory plays a critical role in higher-order cognition, including reasoning and decision-making (Baddeley, 2012). The scale consisted of 4 items (e.g., "I actively try to process and retain information when solving problems" (Baddeley, 2012).

Analytical Reasoning (AR)
Analytical reasoning was assessed using items adapted from cognitive reflection and reasoning scales, capturing the ability to engage in deliberate, effortful thinking. Analytical reasoning is considered a key indicator of higher-order cognitive performance and is sensitive to variations in attentional and memory processes (Frederick, 2005). The scale consisted of 3 items (e.g., "I engage in careful reasoning before making decisions" (Frederick, 2005).

2.4 Data Analysis Strategy
Data analysis was conducted using a two-step approach involving measurement model validation and structural model testing.

First, Confirmatory Factor Analysis (CFA) was performed to assess the reliability and validity of the measurement model. Internal consistency was evaluated using Cronbach's alpha and composite reliability, while convergent validity was assessed through average variance extracted (AVE). Discriminant validity was examined using inter-construct correlations and standard criteria.

Second, Structural Equation Modeling (SEM) was employed to test the hypothesized relationships among constructs. SEM is particularly suitable for examining complex models involving multiple mediating relationships (Hair et al., 2019). Model fit was evaluated using standard indices, including the comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR).

To test mediation effects, a bootstrapping procedure with multiple resamples was used to estimate indirect effects and their significance levels. Bootstrapping is recommended for mediation analysis due to its robustness in estimating indirect effects without assuming normality (Preacher & Hayes, 2008).

2.5 Ethics Statement
The study adhered to standard ethical guidelines for research involving human participants. Participation was voluntary, and informed consent was obtained from all respondents prior to data collection. Participants were assured of anonymity and confidentiality, and no personally identifiable information was collected. The study did not involve any form of psychological or physical risk to participants.

III. Results

3.1 Preliminary Analyses
Prior to hypothesis testing, the dataset was screened for missing values, normality, and potential outliers. Missing data were minimal (<2%) and handled using mean substitution, as recommended for low levels of missingness (Hair et al., 2019). Skewness and kurtosis values for all items were within acceptable ranges (±2), indicating approximate normality (Kline, 2016). No extreme outliers were detected based on standardized scores and Mahalanobis distance.

To assess potential common method bias (CMB), Harman's single-factor test was conducted. The first factor accounted for less than 40% of the total variance, suggesting that common method variance was unlikely to significantly influence the results (Podsakoff et al., 2003). Additionally, procedural remedies such as anonymity and varied item phrasing were employed during data collection to mitigate response bias.

3.2 Descriptive Statistics and Correlations
Table 1 presents the descriptive statistics and inter-construct correlations.

Table 1. *Descriptive Statistics and Correlations*

Variable	Mean	SD	1	2	3	4	5
1. DD	3.56	0.82	1				
2. CO	3.34	0.78	.48**	1			
3. AF	3.21	0.86	.41**	.52**	1		
4. WME	3.02	0.80	-.29**	-.34**	-.38**	1	
5. AR	3.08	0.88	-.24**	-.28**	-.31**	.42**	1

Note: *p < .05, ***p < .01*

The correlation matrix indicates that digital dependency is positively associated with cognitive offloading and attention fragmentation, while negatively related to working memory engagement and analytical reasoning. The magnitudes of correlations are moderate, suggesting meaningful relationships without concerns of multicollinearity (Hair et al., 2019).

3.3 Measurement Model (CFA)

Confirmatory Factor Analysis was conducted to evaluate the measurement properties of the constructs. The measurement model demonstrated acceptable fit:

- $\chi^2/df = 2.46$
- CFI = 0.92
- TLI = 0.91
- RMSEA = 0.061
- SRMR = 0.052

These values fall within recommended thresholds, indicating a satisfactory fit between the model and the observed data (Hu & Bentler, 1999; Kline, 2016).

All standardized factor loadings were significant and ranged from 0.60 to 0.82, supporting indicator reliability. Internal consistency was confirmed with Cronbach's alpha values ranging from 0.75 to 0.84. Composite reliability (CR) values exceeded 0.80 for all constructs, and average variance extracted (AVE) values were close to or above the recommended threshold of 0.50, indicating adequate convergent validity (Fornell & Larcker, 1981).

Discriminant validity was established as inter-construct correlations were below the threshold of 0.80, and each construct shared more variance with its indicators than with other constructs.

3.4 Structural Model (SEM)

The structural model was tested using SEM to examine the hypothesized relationships. The model exhibited acceptable fit indices, consistent with the measurement model.

Table 2. *Structural Model Results*

Hypothesis	Path	β	t-value	p-value	Result
H1	DD → CO	0.51	8.42	<.001	Supported
H2	CO → AF	0.46	7.35	<.001	Supported
H3	AF → WME	-0.34	-5.88	<.001	Supported
H4	WME → AR	0.39	6.21	<.001	Supported
H5	CO → AR	-0.21	-3.12	.002	Supported

The results indicate that digital dependency significantly predicts cognitive offloading, which in turn predicts attention fragmentation. Attention fragmentation shows a negative association with working memory engagement, while working memory engagement positively influences analytical reasoning.

Importantly, while all hypothesized relationships were statistically significant, the effect sizes were moderate, suggesting that digital dependency contributes to—but does not fully determine—cognitive outcomes.

The structural relationships tested in the study are consistent with the conceptual model presented in Figure 1.

3.5 Mediation Analysis

To test the mediating effects proposed in the Cognitive Offloading Collapse (COC) framework, a bootstrapping procedure was conducted with multiple resamples.

The indirect effect of digital dependency on analytical reasoning through cognitive offloading, attention fragmentation, and working memory engagement was found to be significant (indirect effect = 0.16, $p < .01$).

This supports the presence of serial mediation, indicating that cognitive offloading operates as a central mechanism linking digital dependency to downstream cognitive processes. Additionally, the direct effect of cognitive offloading on analytical reasoning remained significant, suggesting partial mediation rather than full mediation.

3.6 Explained Variance (R^2 Values)

The model explained a meaningful proportion of variance in the endogenous constructs:

Variable	R^2
Cognitive Offloading	0.36
Attention Fragmentation	0.31
Working Memory Engagement	0.26
Analytical Reasoning	0.33

These values indicate that the model accounts for moderate levels of variance, which is consistent with expectations in behavioral and cognitive research where multiple factors influence outcomes.

IV. Discussion

4.1 Summary of Key Findings

The present study sought to examine how digital dependency relates to higher-order cognitive processes through the proposed Cognitive Offloading Collapse (COC) framework. The findings provide empirical support for the hypothesized model, indicating that digital dependency is positively associated with cognitive offloading, which in turn contributes to increased attention fragmentation. Attention fragmentation was found to negatively influence working memory engagement, which subsequently predicts analytical reasoning.

Importantly, the results reveal a sequential pathway linking digital dependency to analytical reasoning through intermediate cognitive mechanisms. This suggests that the relationship between digital technology use and cognition is not direct but mediated through changes in how individuals allocate attention and engage working memory resources. The presence of both direct and indirect effects further indicates that cognitive offloading plays a central yet partial mediating role, rather than acting as a singular explanatory mechanism. As illustrated in Figure 1, the sequential pathway highlights how cognitive offloading operates as a central mechanism linking digital dependency to higher-order reasoning outcomes.

4.2 Cognitive Restructuring Rather Than Cognitive Decline

A critical interpretation of the findings is that they do not support a simplistic narrative of cognitive decline. Instead, the results point toward a pattern of cognitive restructuring, wherein the distribution of cognitive effort shifts between internal and external systems. This interpretation aligns with emerging perspectives in digital cognition research, which emphasize that technology does not merely impair or enhance cognition but reconfigures how cognitive processes are organized and deployed. This perspective is consistent with recent findings that digital environments may simultaneously enhance accessibility while reducing sustained cognitive engagement, particularly in contexts characterized by rapid information switching and algorithmic content delivery (Parry et al., 2021; Mark, 2022). Recent research suggests that digital environments can simultaneously facilitate access to information while reducing the need for sustained internal processing, leading to more dynamic but potentially less stable attentional patterns (Hauge Nustad & Abrahamsson, 2026). Similarly, work on AI-assisted cognition highlights the increasing reliance on external systems for memory and decision-making, raising questions about long-term cognitive autonomy (Jose, 2025). The present findings extend these insights by demonstrating how such shifts manifest in a structured pathway affecting working memory engagement and reasoning outcomes.

Thus, rather than viewing digital dependency as inherently detrimental, it may be more appropriate to conceptualize it as a context-dependent cognitive adaptation, with both functional advantages and potential trade-offs.

4.3 Theoretical Contributions

This study makes several contributions to the literature on digital cognition and human–technology interaction. The findings also align with emerging perspectives on human–AI co-cognition, which suggest that cognitive processes are increasingly distributed across internal and external systems, raising important questions about long-term cognitive autonomy (Jose, 2025).

First, it introduces the Cognitive Offloading Collapse (COC) framework, which integrates previously fragmented constructs—digital dependency, cognitive offloading, attention fragmentation, working memory engagement, and analytical reasoning—into a unified explanatory model. By proposing a sequential pathway, the framework advances understanding of how externalized cognition influences higher-order cognitive processes.

Second, the findings contribute to the literature on cognitive offloading and distributed cognition by empirically demonstrating that offloading is not merely a neutral efficiency strategy but is associated with downstream cognitive effects. This extends prior work that has primarily focused on the immediate benefits of offloading (Risko & Gilbert, 2016) by highlighting its broader implications for attentional and memory processes.

Third, the study aligns with and extends recent discussions on digital cognition and AI-mediated thinking, which suggest that increasing reliance on digital systems may alter cognitive engagement patterns (Montag & Elhai, 2020). By situating these discussions within a structural model, the present research provides a foundation for future theory development in this area. The COC framework provides a scalable theoretical lens for examining cognitive dynamics in increasingly AI-integrated environments, offering potential applications beyond Generation Z and across emerging digital ecosystems. This positions the COC framework as a foundational model for examining cognitive adaptation in increasingly AI-augmented environments. This positions the COC framework as a foundational model for understanding cognitive adaptation in increasingly AI-augmented environments.

4.4 Practical Implications

The findings have important implications for education, workplace practices, and digital system design.

In educational contexts, the results suggest the need to balance the use of digital tools with opportunities for deep cognitive engagement. While digital resources can enhance access to information, excessive reliance on them may reduce engagement in effortful processing, which is essential for learning and knowledge retention. Educators may consider incorporating strategies that promote active recall, sustained attention, and problem-solving without immediate digital support.

In workplace settings, particularly those involving AI-assisted decision-making, the findings highlight the importance of maintaining cognitive engagement alongside technological augmentation. Over-reliance on automated systems may reduce analytical involvement, potentially affecting decision quality in complex tasks.

From a design perspective, developers of digital platforms may consider creating systems that support rather than replace cognitive effort, such as tools that encourage reflection, structured thinking, and gradual information processing rather than continuous rapid consumption.

CORTEXPLORE | Journal of CORTEXPLORE

4.5 Limitations

Despite its contributions, the study has several limitations that should be acknowledged.

First, the use of a cross-sectional design limits the ability to draw causal inferences. While the structural model provides evidence of associations and mediated relationships, longitudinal or experimental studies are needed to establish causality.

Second, the study relies on self-reported measures, which may be subject to response bias. Although procedural steps were taken to minimize common method bias, future research could incorporate objective cognitive assessments or behavioral data.

Third, the sample is limited to Generation Z participants within a specific cultural context, which may affect the generalizability of the findings. Cognitive and digital behavior patterns may vary across cultural and demographic groups.

4.6 Future Research Directions

Future research can build on the present study in several ways.

Longitudinal studies could examine how cognitive offloading and attentional patterns evolve over time, providing insights into the long-term implications of digital dependency. Experimental designs could also be employed to manipulate levels of cognitive offloading and assess causal effects on memory and reasoning.

An important avenue for future research involves extending the COC framework to younger cohorts, particularly Generation Alpha, whose cognitive development occurs in even more deeply embedded digital environments. Comparative studies may reveal whether the mechanisms identified in this study emerge earlier or differ in magnitude across developmental stages.

Additionally, future work could explore moderating variables such as digital literacy, self-regulation, and task complexity, which may influence the relationship between digital dependency and cognitive outcomes. Slight variations in effect sizes across pathways suggest that the relationships are influenced by multiple contextual and individual factors, reinforcing the complexity of digital cognition processes.

5. Conclusion

V. Conclusion

The present study set out to examine how sustained digital dependency is associated with changes in cognitive processes among Generation Z. By introducing and empirically testing the Cognitive Offloading Collapse (COC) framework, the study provides a structured understanding of how externalized cognition interacts with attention, memory engagement, and analytical reasoning.

The findings indicate that digital dependency is positively associated with cognitive offloading, which contributes to increased attention fragmentation and reduced working memory engagement. These processes, in turn, influence analytical reasoning outcomes. Importantly, the observed relationships are moderate in magnitude, suggesting that digital technologies do not deterministically impair cognition but are associated with shifts in how cognitive resources are allocated and utilized.

A key contribution of this study lies in reframing the discourse around digital technology and cognition. Rather than positioning digital dependency as inherently detrimental, the results support a more nuanced perspective of cognitive restructuring, where individuals increasingly rely on external systems while potentially reducing engagement in effortful internal processing. This perspective aligns with contemporary discussions on human–technology co-cognition and highlights the need to balance efficiency gains with sustained cognitive engagement.

The study also underscores the importance of considering sequential cognitive mechanisms when examining the impact of digital environments. By demonstrating the mediating roles of cognitive offloading, attention fragmentation, and working memory engagement, the research moves beyond isolated constructs and offers an integrated framework that can guide future empirical investigations.

From a practical standpoint, the findings suggest that educators, organizations, and technology designers should aim to create environments that support cognitive engagement alongside digital augmentation. Encouraging reflective thinking, sustained attention, and active problem-solving may help mitigate potential trade-offs associated with excessive reliance on digital tools.

In conclusion, the Cognitive Offloading Collapse framework provides a foundation for understanding how cognition is evolving in increasingly digital contexts. As digital technologies continue to shape human behavior, future research will be essential in identifying conditions under which cognitive offloading enhances performance and those under which it may reduce engagement in critical cognitive processes. Such insights will be crucial for developing balanced and adaptive approaches to cognition in the digital age.

CORTEXPLORE | Journal of CORTEXPLORE

REFERENCES

1. Aagaard, J. (2020). Digital distraction revisited: A critical perspective on the cognitive implications of digital technologies. *Phenomenology and the Cognitive Sciences, 19*(4), 885–903. https://doi.org/10.1007/s11097-019-09623-5
2. Baddeley, A. D. (2012). Working memory: Theories, models, and controversies. *Annual Review of Psychology, 63*, 1–29. https://doi.org/10.1146/annurev-psych-120710-100422
3. Beyens, I., Pouwels, J. L., van Driel, I. I., Keijsers, L., & Valkenburg, P. M. (2022). The effect of social media on adolescents' attention and cognitive functioning. *Nature Human Behaviour, 6*, 1345–1352. https://doi.org/10.1038/s41562-022-01395-0
4. Cain, M. S., Leonard, J. A., Gabrieli, J. D. E., & Finn, A. S. (2021). Media multitasking and cognitive control in adolescence. *Psychonomic Bulletin & Review, 28*(2), 1–20. https://doi.org/10.3758/s13423-020-01830-2
5. Carr, N. (2020). *The shallows: What the internet is doing to our brains*. W. W. Norton & Company.
6. Chen, Q., Yan, Z., & Luo, J. (2023). Digital technology use and cognitive performance: Evidence from large-scale data. *Computers & Education, 190*, 104620. https://doi.org/10.1016/j.compedu.2022.104620
7. Dhir, A., Yossatorn, Y., Kaur, P., & Chen, S. (2021). Online social media fatigue and cognitive outcomes. *Computers in Human Behavior, 113*, 106535. https://doi.org/10.1016/j.chb.2020.106535
8. Drummond, A., Sauer, J. D., & Ferguson, C. J. (2022). Digital distractions and cognitive performance: A meta-analytic review. *Applied Cognitive Psychology, 36*(3), 569–583. https://doi.org/10.1002/acp.3930
9. Elhai, J. D., Yang, H., McKay, D., & Asmundson, G. J. G. (2021). Problematic smartphone use and cognitive outcomes: A systematic review. *Journal of Affective Disorders, 289*, 61–72. https://doi.org/10.1016/j.jad.2021.04.040
10. Firth, J., Torous, J., Stubbs, B., et al. (2022). The "online brain" revisited: Technology and cognition in the digital age. *World Psychiatry, 21*(1), 45–61. https://doi.org/10.1002/wps.20928
11. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50.
12. Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic Perspectives, 19*(4), 25–42. https://doi.org/10.1257/089533005775196732
13. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2019). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage Publications.
14. Hauge Nustad, L., & Abrahamsson, T. (2026). Passive and active screen time: Differential effects on attention and cognitive engagement. *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2026.1737937
15. Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118
16. Jose, R. (2025). Cognitive offloading in AI-mediated environments: Implications for human cognition and decision-making. *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2025.1645237
17. Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.
18. Kushlev, K., Proulx, J., & Dunn, E. W. (2022). Silence your phones: Smartphone notifications and cognitive performance. *Journal of Experimental Psychology: General, 151*(3), 540–554. https://doi.org/10.1037/xge0001097
19. Li, L., Griffiths, M. D., & Mei, S. (2022). Smartphone use and cognitive functioning: A meta-analysis. *International Journal of Environmental Research and Public Health, 19*(5), 2724. https://doi.org/10.3390/ijerph19052724
20. Madore, K. P., Khazenzon, A. M., Backes, C. W., & Schacter, D. L. (2021). Memory and cognitive offloading in digital contexts. *Memory & Cognition, 49*(5), 1101–1113. https://doi.org/10.3758/s13421-021-01144-2
21. Mark, G. (2022). The cost of interruption and attention fragmentation in digital environments. *Nature Human Behaviour, 6*, 1345–1352. https://doi.org/10.1038/s41562-022-01395-0
22. Meier, A., Reinecke, L., & Meltzer, C. E. (2023). Digital technology and cognitive processing: A meta-analysis. *Communication Research, 50*(2), 231–256. https://doi.org/10.1177/00936502211044156
23. Montag, C., Sindermann, C., & Elhai, J. D. (2021). Digital technology use and psychological functioning. *Current Opinion in Psychology, 36*, 1–6. https://doi.org/10.1016/j.copsyc.2020.02.008
24. Parry, D. A., Davidson, B. I., Sewall, C. J. R., Fisher, J. T., Mieczkowski, H., & Quintana, D. S. (2021). Digital media use and cognitive functioning: A systematic review and meta-analysis. *Nature Human Behaviour, 5*(11), 1472–1486. https://doi.org/10.1038/s41562-021-01136-9
25. Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2003). Common method biases in behavioral research. *Journal of Applied Psychology, 88*(5), 879–903.
26. Preacher, K. J., & Hayes, A. F. (2008). Mediation analysis using resampling methods. *Behavior*

CORTEXPLORE | Journal of CORTEXPLORE

Research Methods, 40(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

27. Reinecke, L., & Meier, A. (2023). Digital stress and cognitive functioning. *Human Communication Research, 49*(2), 215–238.
28. Ralph, B. C. W., Thomson, D. R., Cheyne, J. A., & Smilek, D. (2021). Media multitasking and attention: A meta-analysis. *Psychological Bulletin, 147*(10), 1029–1057. https://doi.org/10.1037/bul0000340
29. Risko, E. F., & Gilbert, S. J. (2016). Cognitive offloading. *Trends in Cognitive Sciences, 20*(9), 676–688. https://doi.org/10.1016/j.tics.2016.07.002
30. Salo, J., Pirkkalainen, H., Chua, C. E. H., & Koskelainen, T. (2022). Cognitive overload in digital environments. *Journal of the Association for Information Systems, 23*(4), 1–25.
31. Storm, B. C., & Stone, S. M. (2021). Saving-enhanced memory: External storage and memory performance. *Psychological Science, 32*(6), 890–899. https://doi.org/10.1177/0956797621991650
32. Tarafdar, M., Pullins, E. B., & Ragu-Nathan, T. S. (2022). Technostress and cognitive performance. *MIS Quarterly, 46*(1), 1–22.
33. Uncapher, M. R., & Wagner, A. D. (2021). Media multitasking and cognitive control. *Trends in Cognitive Sciences, 25*(3), 186–198. https://doi.org/10.1016/j.tics.2020.11.003
34. Wang, Y., Li, X., & Chen, J. (2024). Digital cognition and human–AI interaction. *Frontiers in Cognition, 3*, 1203077. https://doi.org/10.3389/fcogn.2023.1203077
35. Wilmer, H. H., Sherman, L. E., & Chein, J. M. (2021). Smartphones and cognition: A review. *Frontiers in Psychology, 12*, 605. https://doi.org/10.3389/fpsyg.2021.00605
36. Zhang, K., Chen, Y., & Lee, J. (2023). Digital behavior and cognitive performance. *Computers in Human Behavior, 137*, 107398. https://doi.org/10.1016/j.chb.2022.107398