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The Cognitive Costs of AI: Burnout and Executive Functioning in Higher Education

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Abstract

Generative artificial intelligence (AI) has rapidly entered higher education, raising questions about its impact on students' psychological and cognitive functioning. While AI tools promise efficiency, their integration may amplify existing strains such as digital burnout and weaken executive functioning (EF). This study examined the relationships among digital burnout, EF, and AI use among university students.

A cross-sectional online survey was conducted with 401 participants aged 18–35 years (197 female, 192 male, 2 non-binary, 10 prefer not to say). Measures included the Burnout Assessment Tool (BAT-22), the Barkley Deficits in Executive Functioning Scale–Short Form (BDEFS-SF), and an adapted AI Use and Perceived Usefulness scale. Analyses comprised descriptive statistics, correlations, reliability checks, *t*-tests, and multiple regression.

Results indicated strong internal reliability for all measures ($\alpha \geq .85$). Higher burnout predicted greater EF difficulties ($\beta = .88$, $p < .001$). AI users ($n = 332$) reported significantly higher burnout ($M = 82.05$, $SD = 16.26$) and EF deficits ($M = 60.44$, $SD = 11.91$) compared to non-users ($n = 69$), with very large effect sizes (Cohen's $d > 1.80$). Perceived AI usefulness also predicted EF difficulties ($\beta = .17$, $p = .008$) but did not moderate the burnout–EF relationship.

These findings suggest that while AI may be perceived as supportive, its use is associated with greater burnout and EF impairments. Universities should therefore promote mindful integration of AI and provide interventions to safeguard cognitive and psychological resilience.

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INTRODUCTION

Human knowledge has always been shaped by tools that extend thought—from writing and the codex to the printing press and the internet. Each shift has transformed not just access to information but the conditions of learning itself. Generative artificial intelligence is the latest transformation, raising questions about how students sustain effort, balance external aids with internal capacities, and engage authentically with knowledge.

Plato's Allegory of the Cave captures this tension between illusion and truth. Just as prisoners mistook shadows for reality, today's students, tethered to screens, encounter AI systems such as ChatGPT, Gemini, and Perplexity. These tools can ease burdens and accelerate learning, yet risk replacing genuine cognitive engagement. This duality frames the present study's focus: how AI use intersects with students' executive functioning and psychological well-being.

In the past decade, university students' reliance on digital technologies has surged. While essential for academic work, devices and platforms are also linked to distraction, overload, and fatigue (Montag & Elhai, 2020; Salmela-Aro & Upadyaya, 2020). This strain is captured by *digital burnout*—exhaustion, cynicism, and reduced accomplishment arising from constant digital demands (Schaufeli et al., 2002; Salmela-Aro & Read, 2017).

Burnout has clear cognitive consequences, particularly for executive functioning (EF)—the higher-order processes supporting planning, attention, time management, and impulse control (Diamond, 2013). EF is vital for student success yet vulnerable to chronic stress. Burnout and EF deficits reinforce one another: exhaustion depletes cognitive resources, while impaired EF hinders regulation and adaptation (Zelazo, Blair, & Willoughby, 2016). This reciprocity underscores the need to examine their intersection in higher education.

Generative AI introduces a new dimension to learning. While early studies suggest it can reduce cognitive load and redistribute effort (Holstein et al., 2020; Gkintoni et al., 2025; Chen et al., 2025), most focus on efficiency, leaving psychological outcomes such as burnout and their link to executive functioning (EF) underexplored. For university students, who juggle autonomy, academic demands, and digital saturation, this gap is pressing.

Theoretical perspectives offer competing predictions. Cognitive offloading suggests AI may extend cognition by freeing resources for higher-order reasoning (Risko & Gilbert, 2016), yet over-reliance may erode internal capacities. From a burnout lens, AI could buffer strain by easing workload or amplify it through deeper digital immersion. Student accounts capture this ambivalence—balancing convenience against stress, dependence, and fatigue.

Research on AI, burnout, and executive functioning (EF) remains scarce. While digital media overuse has been linked to cognitive failures and reduced achievement (Ma et al., 2025; Özalp, 2025), few studies address AI directly. Klarin et al. (2024) examined adolescents, but evidence from university settings is lacking.

This study therefore aimed to: (1) examine associations between burnout and EF; (2) test whether AI use relates to differences in burnout and EF; (3) identify EF domains most affected under high burnout; and (4) assess whether perceived AI usefulness moderates the burnout–EF link. It was hypothesized that burnout would predict EF deficits (H1), frequent AI users would show higher burnout (H2) and lower EF (H3), and AI usefulness would moderate the burnout–EF relationship (H4).

Generative AI thus represents both light and shadow: a Promethean fire that illuminates knowledge yet risks overwhelming learners. As in Plato's allegory, students must discern authentic learning amid digital abundance.

Review of Literature

AI, Cognitive Load & Cognitive Offloading

Generative AI reshapes how students approach effort. Reviews and experiments (Seung, 2024; Kosmyna et al., 2025; Bai et al., 2023) show it reduces surface effort and personalizes learning, but may weaken memory and critical thinking. Empirical work (Gerlich, 2025; Singh et al., 2025) confirms this paradox: AI boosts efficiency yet promotes cognitive offloading, reallocating effort from internal processing to external scaffolds. This eases immediate tasks but undermines long-term resilience.

Digital Addiction & Academic Burnout/Well-Being

Digital and social media overuse consistently predicts burnout, fatigue, and disengagement (AlJemely, 2024; Mariappan et al., 2025; Ma et al., 2025). Emotional disturbance, poor sleep, and social comparison mediate these links (Zhang et al., 2023; Abraham et al., 2025). Even protective factors like academic passion fail to offset the strain. The mechanism reflects a strain–outcome cycle where overstimulation drains regulation, escalating stress despite temporary engagement.

AI Use & Academic Outcomes

Findings on ChatGPT are mixed. Structural modelling (Ashraf et al., 2025) links habit and enjoyment to higher performance via behavioural intentions. Yet others (Uppal & Hajian, 2025; Zhang et al., 2024; Barton et al., 2024) highlight trade-offs: dependency and procrastination rise alongside perceived reliability. Outcomes hinge on motivation: curiosity-driven use promotes self-regulated learning, while expediency-driven reliance fosters shortcuts and disengagement.

Digital Interventions & Mental Health

AI-driven interventions reduce loneliness, anxiety, and depression (Madrid-Cagigal et al., 2025; Mushtaq, 2025; Fang et al., 2025). Chatbots improve regulation and social cognition, and automated interventions rival guided formats. Yet prolonged use risks dependency, as gains in accessibility may erode without human interaction. This reflects stepped-care models: short-term relief is feasible, but balance is essential.

Machine Learning & Stress Detection

Machine learning shows promise for stress detection, achieving up to 95% accuracy with multidimensional indicators (Singh et al., 2024; Das et al., 2025). However, limited personalization and real-time adaptation restrict practical application. While strong in pattern recognition, current systems risk misclassifying individual differences.

Special/Emerging Educational Contexts

Emerging tools like VR, ICT, and gamification show potential but carry risks. VR enhances outcomes when cognitive presence is optimized; ICT and robotics boost motivation for neurodiverse learners; and gamification reduces cognitive load compared to AI (Wei et al., 2025; Fernández-Batanero et al., 2024; Khasawneh & Khasawneh, 2024; Alarabiat, 2024). Yet online fatigue studies caution that excessive digital engagement diminishes motivation. Effectiveness depends on design and alignment: technologies succeed when tailored to learner capacity but fail when demands exceed it.

Taken together, existing studies show that digital technologies and AI exert profound yet ambivalent effects on students' cognitive, emotional, and academic lives. They enhance access, efficiency, and motivation but also risk cognitive offloading, dependence, burnout, and disengagement. Overuse erodes executive functioning and well-being, while interventions can ease loneliness and stress yet foster dependency when relied on excessively. Machine learning advances stress detection but require personalization, and tools for neurodiverse learners or VR environments reveal both potential and vulnerability depending on design. Overall, technology's impact is contingent not on the tools themselves but on patterns of use, mediating mechanisms, and contextual fit.

Methodology

Research Design

The study used a quantitative, cross-sectional correlational design to examine relationships among digital burnout, executive functioning (EF), and generative artificial intelligence (AI) use in university students. A cross-sectional survey enabled efficient data collection from a large sample at one time point, making it suitable for assessing patterns of association in academic settings (Bryman, 2016). A correlational approach aligned with the study's exploratory aim, focusing on associations and potential moderation rather than causal inference.

Aim:

To examine the interrelationships between digital burnout, executive functioning (EF), and generative artificial intelligence (AI) use among university students.

Hypotheses

- **H1:** Higher levels of digital burnout will be associated with greater executive functioning (EF) deficits.
- **H2:** Frequent users of generative AI tools will report higher levels of digital burnout compared to infrequent or non-users.
- **H3:** Frequent users of generative AI tools will report greater EF deficits compared to infrequent or non-users.
- **H4:** Perceived usefulness of generative AI will moderate the relationship between digital burnout and EF deficits, such that the negative association between burnout and EF will be weaker among students who perceive AI tools as highly useful.

Participants

A total of 401 university students participated in the study. The sample consisted of 197 females (49.1%), 192 males (47.9%), 2 non-binary individuals (0.5%), and 10 participants (2.5%) who preferred not to disclose their gender. Participants' ages ranged from 18 to 35 years (M = 24.0, SD ≈ 3.6).

Table 1: Demographic details according to gender

Total	**401**
Female	197
Male	192
Non-Binary	2
Undisclosed	10

Table 2: Demographic details according to age

Age	**No. of Participants**
18	13
19	9
20	15
21	40
22	50

23	51
24	53
25	50
26	44
27	29
28	14
29	9
30	4
31	5
32	7
33	3
35	5

Participants were recruited via university mailing lists, student networks, and online platforms. Eligibility required current university enrollment and age 18–35; individuals with neurological or psychiatric conditions affecting EF were excluded. Participation was voluntary with informed consent obtained.

An a priori power analysis (G*Power 3.1) indicated 100–150 participants would suffice to detect medium effects (f^2 = .15, α = .05, power = .80) in regression with up to five predictors. The final sample of 401 therefore provided strong statistical power for the study's aims.

Measures

Burnout

Burnout was measured with the Burnout Assessment Tool – 22 item version (BAT-22; Schaufeli, De Witte, & Desart, 2019), which assesses exhaustion, mental distance, cognitive impairment, and emotional impairment. Items (e.g., "I feel mentally exhausted") were rated on a 5-point Likert scale (1 = never to 5 = always), with higher scores indicating greater burnout. The BAT-22 has shown strong reliability and validity; in this study, Cronbach's alpha was calculated for subscales and the total score.

Executive Functioning

Executive functioning (EF) was measured using the **BDEFS-SF (Barkley Deficits in Executive Functioning Scale – Short Form; Barkley, 2011)**. This scale assesses self-reported difficulties across domains such as time management, organization, self-motivation, emotional regulation, and self-restraint. Items are rated on a Likert scale ranging from *1 = never or rarely* to *4 = very often*. Higher scores reflect greater executive dysfunction. The BDEFS-SF has been widely used in both clinical and non-clinical adult samples and demonstrates high internal consistency and convergent validity with performance-based EF tasks.

AI Use and Perceived Usefulness

AI use was assessed with a modified version of Klarin, Hoff, Larsson, and Daukantaitė's (2024) scale, adapted from schoolwork to university assignments. Items measured frequency of use, types of tools, and perceived usefulness (e.g., "AI tools help me get started with assignments," "AI tools help me structure my work"). Responses were given on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree), with higher scores indicating greater perceived usefulness.

Procedure

Data were collected through an online survey created in Google Forms. Participants were first presented with an informed consent form outlining the purpose of the study, their rights as participants, and assurances of confidentiality and voluntary participation. Only individuals who provided consent proceeded to the survey.

The survey was structured into sections in the following order:

1. **Executive Functioning (BDEFS-SF):** Participants completed the Barkley Deficits in Executive Functioning Scale – Short Form, which assessed self-reported EF difficulties.
2. **Burnout (BAT-22):** The Burnout Assessment Tool – 22 item version was then administered to measure levels of exhaustion, mental distance, cognitive impairment, and emotional impairment.
3. **AI Use:** Following the burnout scale, participants were asked whether they used AI tools (e.g., ChatGPT, Gemini, Perplexity) for academic work. If they selected "Yes," they proceeded to the adapted AI use and perceived usefulness questionnaire (based on Klarin et al., 2024). If they selected "No," the survey ended.
4. **Demographics:** Age, gender, and other background details were collected at the beginning of the survey to describe the sample.

The average completion time was approximately **8–10 minutes**. To minimize participant fatigue, items were grouped by construct, and clear instructions were provided at the start of each section. Responses were automatically recorded and exported into a secure database accessible only to the researcher. Data were screened for completeness prior to analysis, and incomplete submissions were excluded.

Qualitative item analysis. Participants listed chatbots used and shared open-ended comments about AI use. Responses were analysed inductively following Braun and Clarke's (2006) thematic approach: data familiarization, coding of recurring features, and clustering into themes (e.g., academic support, practical planning, emotional support, creativity, decision-making, social surrogate use, guilt/awareness, and none). Representative anonymized quotes were included to contextualize quantitative findings, though the analysis was not intended as a full qualitative study.

Results

This chapter presents the findings of the study in line with the stated objectives and hypotheses. Results are organized into six sections: (1) preliminary analyses, (2) descriptive statistics, (3) reliability analyses, (4) correlations among main variables, (5) group comparisons, (6) regression analyses, and (7) moderation analysis.

Preliminary Analyses

Data were screened for accuracy, missing values, and outliers. Although Shapiro–Wilk tests indicated non-normality (*ps*< .001), skewness and kurtosis (–2 to +2), histograms, and Q–Q plots suggested approximate normality. With a large sample (N = 401), parametric analyses were considered appropriate.

Participants reported diverse AI chatbot use: ChatGPT (91.9%) and Google Bard/Gemini (95.8%) were most common, followed by Perplexity (46.1%), BlackBox (8.7%), and My AI on Snapchat (7.8%) (see Table 3).

Table 3: *Chatbot usage frequencies*

Chatbot	Frequency	Percentage
Google Bard/Gemini	318	95.8
ChatGPT	305	91.9
Other/ Perplexity	153	46.1
BlackBox	29	8.7
My AI (Snapchat)	26	7.8
Socratic	19	5.7
YouChat	2	0.6

In addition to closed-ended items, participants responded to open-ended questions about how they use AI. The responses clustered into several themes: *academic support, practical planning, emotional support/venting, creative uses, decision-making,* and *social surrogate uses.* Representative themes are summarized in Table 4; selected anonymized quotations follow.

Table 4: *Themes from open-ended responses about AI use (selected themes and descriptions)*

Theme	Description / example uses
Academic support	Summaries, notes, assignment drafting, revision
Practical planning	Workouts, diet, scheduling, travel planning
Emotional support / Venting	Using AI to express feelings, journal, vent
Creative & ideational	Story prompts, art/painting ideas, roleplay
Decision-making	Weighing pros/cons, comparing options
Social surrogate / Loneliness	Conversational practice, companionship
Guilt / Awareness of overuse	Expressions of regret, inability to stop
No use	Respondents reporting no AI usage

Descriptive Statistics

Means, standard deviations, ranges, skewness, and kurtosis values for executive functioning (BDEFS-SF), burnout (BAT-22), and AI use and usefulness (AI-RS) are presented in Table 5.

Table 5: *Descriptive statistics for main variables*

Variable	Mean	SD	Range	Skewness	Kurtosis
Executive Functioning (BDEFS-SF)	56.73	14.09	20-80	-0.59	-0.72
Burnout (BAT-22)	76.39	20.36	22-110	-0.73	-0.52
AI Usefulness (AI-RS)	27.23	13.52	0-45	-1.2	0.09

Reliability Analyses

Internal consistency reliability was assessed using Cronbach's alpha. All measures demonstrated good to excellent reliability: BDEFS-SF (α = .95), BAT-22 (α = .97), and AI-RS (α = .85). Reliability coefficients are reported in Table 6.

Table 6 : *Reliability of scales*

Scale	Items	Cronbach's α
BDEFS-SF	20	0.948
BAT-22	22	0.968
AI-RS	9	0.846

Correlations Among Main Variables

Pearson's correlations were conducted to examine associations among burnout, executive functioning, and AI use. Results revealed strong positive associations between burnout and EF deficits (r = .88, p< .001), burnout and AI use (r = .68, p< .001), and EF deficits and AI use (r = .66, p< .001). Correlation coefficients are presented in Table 7.

Table 7: *Correlations between burnout, EF, and AI use*

Variable	BDEFS-SF	BAT-22	AI-RS
BDEFS-SF	1	0.882**	0.656**
BAT-22	0.882**	1	0.683**
AI-RS	0.656**	0.683**	1

**. Correlation is significant at the 0.01 level (2-tailed).

Group Comparisons: AI Users vs. Non-Users

Independent samples t-tests compared AI users (n = 332) and non-users (n = 69) on burnout and EF. AI users reported significantly higher burnout (M = 82.05, SD = 16.26) compared to non-users (M = 49.16, SD = 15.60), t(101.11) = –15.81, p< .001, Cohen's d = 2.04. Similarly, AI users reported significantly greater EF difficulties (M = 60.44, SD = 11.91) than non-users (M = 38.87, SD = 9.35), t(118.74) = –16.57, p< .001, Cohen's d = 1.87. Group comparisons are summarized in Table 8.

Table 8 : *Group comparisons of AI users and non-users on burnout and EF*

Variable	Non-users M(SD)	Users M(SD)	t(df)	p	Cohen's d
BDEFS-SF	38.87 (9.35)	60.44 (11.91)	-16.57 (118.74)	< .001	1.87
BAT-22	49.16 (15.60)	82.05 (16.26)	-15.81 (101.11)	< .001	2.04

Regression Analyses

Simple Regression

A simple linear regression was conducted to examine whether burnout predicted EF difficulties. Burnout significantly predicted EF, R^2 = .78, F(1, 399) = 1391.57, p< .001, with higher burnout associated with greater EF deficits (B = .61, β = .88, p< .001).

Hierarchical Regression

A hierarchical regression was conducted with EF as the outcome. In Block 1, age and gender explained 4.5% of variance in EF, F(2, 398) = 9.48, p< .001. Burnout was added in Block 2, explaining an additional 73.6% of variance (ΔR^2 = .74, p< .001). In Block 3, AI usefulness significantly predicted EF (β = .17, p = .008), whereas AI use frequency was nonsignificant. The final model explained 78.8% of variance, F(5, 395) = 146.47, p< .001. Regression coefficients are shown in Table 9.

Table 9 : *Hierarchical regression predicting EF difficulties*

Predictor	B	SE B	β	t	p
Burnout (BAT-22)	0.55	0.02	0.8	28.61	<.001
AI Usefulness (AI-RS)	0.18	0.07	0.17	2.66	0.008
Gender	1.07	0.52	0.05	2.05	0.041

Moderation Analysis

Moderation was tested by creating centered variables for burnout and AI usefulness and entering their interaction term. The interaction did not significantly predict EF (B = .002, β = .05, p = .142), indicating that AI usefulness did not moderate the burnout–EF relationship. Full results are reported in Table 10.

Table 10 : *Moderation analysis of AI usefulness on burnout–EF relationship*

Predictor	B	SE B	β	t	p
Burnout (centered)	0.55	0.02	0.8	28.61	< .001
AI Usefulness (centered)	0.18	0.07	0.17	2.66	0.008
Burnout x AI Usefulness	0.002	0.001	0.05	1.47	0.142

Summary of Findings

The analyses revealed that burnout strongly predicted EF deficits, with very large effect sizes. AI users reported significantly higher burnout and EF difficulties than non-users. AI usefulness contributed unique variance in predicting EF, although its moderating role was nonsignificant.

Discussion

Hypothesis-wise Discussion

H1: Higher levels of burnout will be associated with greater EF deficits

This hypothesis was strongly supported. Burnout explained nearly 78% of the variance in EF difficulties, consistent with research linking exhaustion and overload to diminished self-regulation and cognitive flexibility (Ma, Liu, & Zhang, 2025). The strength of this relationship suggests that digital burnout is not merely an emotional state but is deeply entangled with the core executive processes that underpin learning.This quantitative pattern was mirrored in participants' accounts: *"I hate how my phone runs my life… I know it's bad but I can't stop"* — a comment that underlines how digital habits may perpetuate cognitive strain.

The findings recall Kafka's *A Hunger Artist*, whose relentless pursuit of his craft consumed his body until nothing remained but fatigue and emptiness (Kafka, 1922/1995). Burnout, in a similar way, depletes not just emotional energy but the very cognitive structures required to engage with the world. In both cases, the collapse is not dramatic but incremental, a gradual hollowing until the scaffolding of function gives way. For students, what begins as digital over-engagement slowly becomes a corrosion of working memory, planning, and regulation—the cognitive equivalent of Kafka's wasting artist.

H2: Frequent AI users will report higher levels of burnout compared to non-users

H3: Frequent AI users will report greater EF deficits compared to non-users

Both hypotheses were supported. AI users scored significantly higher on both burnout and EF difficulties compared to non-users, with effect sizes (Cohen's $d >$ 1.80) that reflect profound differences between groups. This aligns with emerging concerns that constant engagement with digital tools may exacerbate exhaustion rather than alleviate it (Özalp, 2025).Several respondents described AI as a functional crutch for assignments: *"I use it for assignments and making notes — it speeds up my studying."* Such comments suggest why heavy AI use might accompany higher burnout: ease may encourage overreliance.

The paradox of reliance is illuminated by Borges's tale of *Funes the Memorious*, whose flawless memory rendered him incapable of abstraction or thought (Borges, 1942/2002). Funes could recall every leaf on every tree, yet the very weight of that precision left him paralyzed. Similarly, students who rely on AI may experience immediate relief—outsourced summaries, generated text, simplified tasks—but this very dependency may corrode the deeper faculties of regulation and synthesis. What appears to be a prosthesis of cognition risks becoming its replacement, and, as in Borges's story, the overabundance of external scaffolding may hollow out the vitality of internal thought.

H4: Perceived usefulness of AI will moderate the EF–burnout relationship

This hypothesis was not supported. Although AI usefulness was a significant independent predictor of EF difficulties, its interaction with burnout was nonsignificant. In other words, perceiving AI as useful did not buffer students against the cognitive costs of burnout. Instead, usefulness appeared to intensify engagement with AI, embedding students more deeply in digital environments without mitigating strain.

The result echoes Eliot's lament in *The Love Song of J. Alfred Prufrock*, where life is "measured out in coffee spoons" (Eliot, 1915/2011). Tools of order and convenience do not rescue one from exhaustion; they instead mark the rhythm of depletion, parcelling time into ever finer units until vitality itself feels diminished. Likewise, AI's perceived usefulness may offer precision and ease, yet such comforts do not reverse the erosion of cognitive stamina under burnout. They only structure the erosion, giving it shape without granting reprieve.

Theoretical Implications

The findings extend research on digital burnout and cognition in three ways. First, they confirm the strong link between burnout and EF in university students, supporting burnout's conceptualization as both psychological and cognitive. Second, while AI is often portrayed as reducing workload (Chen et al., 2025; Gkintoni et al., 2025), perceived usefulness here appeared to intensify engagement without easing strain, complicating its role as a supportive resource. Third, the absence of moderation indicates that burnout's impact on EF is consistent regardless of AI utility, suggesting that AI's benefits may be offset by its entanglement with digital fatigue.

These dynamics resonate with Heidegger's notion of *Gestell* (enframing), where technology is not only instrumental but redefines how the world is revealed (Heidegger, 1954/1977). Generative AI, like Heidegger's hydroelectric plant, makes knowledge instantly accessible but risks reducing students to functionaries within the very system that promises their liberation.

Practical Implications

For higher education, the results signal an urgent need to address both digital burnout and student engagement with AI. Universities could offer workshops on digital well-being, focusing on managing screen time, regulating workload, and preserving cognitive boundaries. Rather than discouraging AI, institutions should promote mindful integration, encouraging students to use it as a complement rather than a substitute for effort. Heavy AI users may be turning to it from a place of strain, underscoring the need for targeted academic and psychological support. The use of AI for emotional ventilation — *"I talk to it like a journal when I can't sleep"* — highlights the importance of pairing digital literacy with counselling resources.

This challenge echoes Dostoevsky's *Notes from Underground*, where the narrator rejects the "crystal palace" of rational progress because it threatens autonomy (Dostoevsky, 1864/1993). Likewise, AI's conveniences risk fostering passivity, offering ease at the cost of resilience. Institutions must therefore balance: uncritical embrace may produce passive learners, while outright rejection denies access to a ubiquitous tool. The task is to cultivate a pedagogy where technology supports without engulfing, preserving autonomy within structures that promise ease.

Limitations and Future Directions

Several limitations should be noted. First, reliance on self-report introduces risks of social desirability and perception biases. Second, the cross-sectional design prevents causal inference; it remains unclear whether burnout drives AI use and EF deficits or vice versa. Third, despite large effect sizes, replication is needed to confirm whether magnitudes reflect broader patterns or sample-specific factors. Finally, the AI measure was adapted from adolescent research (Klarin et al., 2024), which may limit generalizability, though reliability was strong here.

Future research should test mediating pathways (e.g., AI use linking burnout and EF), identify domain-specific EF processes most affected by digital overload, and examine cross-cultural differences in AI adoption. Experimental studies could also evaluate interventions that integrate AI support while protecting executive resources.

Conclusion

In sum, this study shows that digital burnout strongly undermines executive functioning in university students and that AI use is linked to higher burnout and EF deficits. While perceived usefulness predicted added variance in EF, it did not moderate the burnout–EF link. These results complicate narratives of AI as purely liberating, instead placing it within the paradox of digital life: a tool of both empowerment and strain.

As Nietzsche warned, "if you gaze long into an abyss, the abyss also gazes into you" (Nietzsche, 1886/1967). Generative AI may be such an abyss—seemingly infinite in knowledge yet mirroring the exhaustion students carry into it. Higher education's task is not to avert this abyss but to equip students to face it without being consumed, fostering resilience, critical engagement, and autonomy in an increasingly mediated landscape.

REFERENCES

Abraham, A., Samy, C., & Kavitha, R. (2025). Digital impact on student well-being: Unravelling the link between online. *International Journal for Multidisciplinary Research, 7.*

Alarabiat, A. (2024). The impact of online learning fatigue on students' continuous use of online learning. *Journal of Theoretical and Applied Information Technology, 102*(20).

AlJemely, Y. A. (2024). Digital addiction and relationship to academic burnout and academic passion. *Well Testing Journal, 33*(S2), 310–325.

Ashraf, M. A., Alam, J., & Kalim, U. (2025). Effects of ChatGPT on students' academic performance in Pakistan higher education classrooms. *Scientific Reports, 15*(1), 16434.

Bai, L., Liu, X., & Su, J. (2023). ChatGPT: The cognitive effects on learning and memory. *Brain-X, 1*(3).

Borges, J. L. (1962). *Labyrinths* (D. A. Yates & J. E. Irby, Eds. & Trans.). New Directions.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101.

Bryman, A. (2016). *Social research methods* (5th ed.). Oxford University Press.

Chen, Y., Wang, Y., Wüstenberg, T., Kizilcec, R. F., Fan, Y., Li, Y., ... &Bärnighausen, T. (2025). Effects of generative artificial intelligence on cognitive effort and task performance: Study protocol for a randomized controlled experiment among college students. *Trials, 26*(1), 244.

Das, S., Nag, S., & Jana, R. (2025). A multimodal systematic review of stress detection in university students based on machine learning and physiological measures.

Diamond, A. (2013). Executive functions. *Annual Review of Psychology, 64*(1), 135–168.

Essel, H. B., Vlachopoulos, D., Essuman, A. B., & Amankwa, J. O. (2024). ChatGPT effects on cognitive skills of undergraduate students: Receiving instant responses from AI-based conversational large language models (LLMs). *Computers and Education: Artificial Intelligence, 6,* 100198.

Fang, C. M., Liu, A. R., Danry, V., Lee, E., Chan, S. W., Pataranutaporn, P., ... & Agarwal, S. (2025). How AI and human behaviors shape psychosocial effects of chatbot use: A longitudinal randomized controlled study.

Fernández-Batanero, J. M., Montenegro-Rueda, M., Fernández-Cerero, J., & López-Meneses, E. (2024). Fostering motivation: Exploring the impact of ICTs on the learning of students with autism. *Children, 11*(1), 119.

Gerlich, M. (2025). AI tools in society: Impacts on cognitive offloading and the future of critical thinking. *Societies, 15*(1), 6.

Gkintoni, E., Antonopoulou, H., Sortwell, A., &Halkiopoulos, C. (2025). Challenging cognitive load theory: The role of educational neuroscience and artificial intelligence in redefining learning efficacy. *Brain Sciences, 15*(2), 203.

Halkiopoulos, C., & Gkintoni, E. (2024). Leveraging AI in e-learning: Personalized learning and adaptive assessment through cognitive neuropsychology—A systematic analysis. *Electronics, 13*(18), Article 3762.

Heidegger, M. (1962). *Being and time* (J. Macquarrie& E. Robinson, Trans.). Harper & Row. (Original work published 1927)

Hesiod. (2006). *Theogony and works and days* (M. L. West, Trans.). Oxford University Press. (Original work ca. 700 BCE)

Holstein, K., Aleven, V., & Rummel, N. (2020). A conceptual framework for human–AI hybrid adaptivity in education.

Kafka, F. (1995). *The trial* (B. Mitchell, Trans.). Schocken Books. (Original work published 1925)

Khasawneh, Y. J., & Khasawneh, M. A. (2024). Cognitive load analysis of adaptive learning technologies in special education classrooms: A quantitative approach. *International Journal of Advanced and Applied Sciences, 11*(12), 34–41.

Klarin, J., Hoff, E., Larsson, A., & Daukantaitė, D. (2024). Adolescents' use and perceived usefulness of generative AI for schoolwork: Exploring their relationships with executive functioning and academic achievement. *Frontiers in Artificial Intelligence, 7,* 1415782.

Kosmyna, N., Hauptmann, E., Yuan, Y. T., Situ, J., Liao, X. H., Beresnitzky, A. V., ... & Maes, P. (2025). Your brain on ChatGPT: Accumulation of cognitive debt when using an AI assistant for essay writing task.

Madrid-Cagigal, A., Kealy, C., Potts, C., Mulvenna, M., Byrne, M., Barry, M., & Donohoe, G. (2024, December). Digital mental health interventions for university students with mental health difficulties. In *CRN and CHilD-RC Annual Conference 2024.*

Ma, X., Liu, Q., & Zhang, W. (2025). The impact of multidimensional excessive social media use on academic performance: The moderating role of mindfulness. *Frontiers in Psychology, 16,* 1579509.

Markauskaite, L., Marrone, R., Poquet, O., Knight, S., Martinez-Maldonado, R., Howard, S., ... & Siemens, G. (2022). Rethinking the entwinement between artificial intelligence and human learning: What capabilities do learners need for a world with AI? *Computers and Education: Artificial Intelligence, 3,* 100056.

Mariappan, K. D., Palayan, S., & Jeganathan, J. (2025). Digital addiction and its relationship with cognitive function among children: A cross-sectional study. *Bioinformation, 21*(5), 1025.

Mushtaq, N. F. (2025). Bridging the gap: The role of AI chatbots in reducing loneliness and improving emotional regulation. *International Journal of Indian Psychology, 13*(1).

Nietzsche, F. (1967). *Beyond good and evil: Prelude to a philosophy of the future* (W. Kaufmann, Trans.). Vintage International. (Original work published 1886)

Özalp, M. (2025). Effect of mobile phone addiction on hand disorder, eye health, fatigue and cognitive failures. *BMC Public Health, 25*(1), 2452.

Plato. (1997). *Complete works* (J. M. Cooper & D. S. Hutchinson, Eds.). Hackett Publishing. (Original work ca. 380 BCE)

Risko, E. F., & Gilbert, S. J. (2016). Cognitive offloading. *Trends in Cognitive Sciences, 20*(9), 676–688.

Salmela-Aro, K., & Upadyaya, K. (2014). School burnout and engagement in the context of the demands–resources model. *British Journal of Educational Psychology, 84*(1), 137–151.

Salmela-Aro, K., & Upadyaya, K. (2020). School engagement and school burnout profiles during high school – The role of socio-emotional skills. *European Journal of Developmental Psychology, 17*(6), 943–964.

Seung, Y. (2024, June 10). The impact of artificial intelligence on cognitive load. *CIDDL – Center for Innovation, Design, and Digital Learning.*

Shiwlani, A., Hasan, S., & Kumar, S. (2024). Artificial intelligence in neuroeducation: A systematic review of AI applications aligned with neuroscience principles for optimizing learning strategies. *Journal of Social Sciences Development, 5,* 578–593.

Singh, A., Taneja, K., Guan, Z., & Ghosh, A. (2025). Protecting human cognition in the age of AI. [Details missing].

Singh, R., Taneja, K., Guan, Z., & Ghosh, A. (2024). [Stress detection via machine learning].

Wei, Z., Liao, J., Lee, L. H., Qu, H., & Xu, X. (2025). Towards enhanced learning through presence: A systematic review of presence in virtual reality across tasks and disciplines.

Zelazo, P. D., Blair, C. B., & Willoughby, M. T. (n.d.). Executive function: Implications for education. NCER 2017-2000. Washington, DC: U.S. Department of Education, Institute of Education Sciences.

Zhang, H., Li, R., Zhang, Y., Xiao, T., Chen, J., Ding, J., & Chen, H. (2025). The evolving role of large language models in scientific innovation: Evaluator, collaborator, and scientist.

Zhang, K., Li, P., Zhao, Y., Griffiths, M. D., Wang, J., & Zhang, M. X. (2023). Effect of social media addiction on executive functioning among young adults: The mediating roles of emotional disturbance and sleep quality. *Psychology Research and Behavior Management, 16,* 1911–1920.

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