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THE IMPACT OF SCREEN TIME AND ARTIFICIAL INTELLIGENCE TOOL USAGE ON ACADEMIC AND PROFESSIONAL PERFORMANCE

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Abstract: The rapid adoption of artificial intelligence (AI) tools has transformed the way students and working professionals perform academic and workplace tasks. However, empirical evidence on the relationship between screen time, AI engagement, and perceived performance remains limited, particularly in exploratory settings. This study investigates the influence of screen time and AI tool usage on perceived academic and professional performance. Data were collected from 45 respondents, comprising college students and working professionals, through a structured online questionnaire. The proposed model examined the relationships among screen time, device usage breadth, AI engagement, AI usage purposes, perceived performance improvement, and screen time growth. The findings reveal that AI has become an integral part of respondents' daily routines, with ChatGPT emerging as the most frequently used AI application. Working professionals reported significantly higher AI usage than full-time students. Most respondents perceived AI tools as enhancing their productivity and academic or professional performance. Furthermore, respondents reported a noticeable increase in overall screen time compared with the previous year, reflecting the growing integration of AI into everyday digital activities. Although several hypothesized relationships were not statistically significant because of the limited sample size, the study offers valuable exploratory evidence on emerging AI usage patterns. The findings contribute to the growing literature on AI adoption by providing preliminary empirical insights while emphasizing the need for larger, more representative samples to validate the proposed relationships**.**

Index Terms **-** Academic Performance, Artificial Intelligence, ChatGPT, Digital Behaviour, Professional Performance, Screen Time and Technology Adoption**.**

I. INTRODUCTION

Smartphones and laptops have become the default interface through which students and professionals study, work, communicate, and unwind, and generative AI tools such as ChatGPT, Gemini, Claude, and Copilot have been adopted into these routines at a pace that has been described as one of the fastest technology-adoption episodes on record, with adoption among some student populations rising from under 10% to over 80% within about two years (Contractor & Reyes, 2025). There are mixed effects of heavy device and screen use on academic and occupational outcomes, sleep, and well-being (Kumban, Cetthakrikul, & Santiworakul, 2025; Liu, Lan, Chen, He, & Jia, 2022).

Two literatures have largely developed in parallel: one on screen time and device use, and a newer one on generative AI adoption and its association with academic or work performance, where evidence remains genuinely mixed — some meta-analytic work finds a positive average effect on academic achievement (Sun & Zhou, 2024), while individual studies report null or negative associations for heavy reliance on AI tools. This study connects the two literatures empirically: it asks whether the intensity and breadth of everyday device use predicts how engaged a person becomes with AI tools, and whether that AI engagement in turn predicts perceived performance benefits and growth in overall screen time. We test this using partial least squares structural equation modeling (PLS-SEM), a variance-based method well suited to small, exploratory samples with a mix of formative and reflective constructs (Hair, Risher, Sarstedt, & Ringle, 2019).

II. LITERATURE REVIEW

Screen time, smartphone usage and everyday functioning

Total daily screen time is a widely used, if coarse, proxy for overall digital engagement. Large cohort work links total smartphone and screen time to elevated academic stress, with smartphone use time and total screen time both positively associated with adolescents' and young adults' academic stress scores (Liu, Lan, Chen, He, & Jia, 2022), while cross-sectional work on university students finds screen time differs by major and study level without a clean association to physical activity or study time (Kumban, Cetthakrikul, & Santiworakul, 2025). A large methodological literature on problematic smartphone use, built on Kwon et al.'s (2013) original Smartphone Addiction Scale, further documents associations between heavy smartphone use and reduced attentional control (Wiradhany & Nieuwenstein, 2017) and elevated anxiety and depression among college students, mediated by attentional bias (Li et al., 2022). A systematic review of media multitasking research similarly concludes that concurrent media use is consistently associated with worse GPA, recall, and reading comprehension, even as students themselves struggle to judge its impact accurately (May & Elder, 2018).

H1: Total screen time is positively associated with AI tool engagement.

Beyond total time, the breadth of purposes for which a person uses their devices (study, social media, entertainment, gaming, office work) may better capture the diversity of digital habits than a single time estimate, and is conceptually related to the media multitasking construct, where use spans multiple concurrent activities and purposes (May & Elder, 2018; Wiradhany & Nieuwenstein, 2017). Users whose device use already spans multiple domains may be more likely to extend that breadth to AI tools as well.

H2: Device usage breadth is positively associated with AI tool engagement.

Technology-adoption perspectives on AI tool engagement

A separate and rapidly growing literature applies established technology-acceptance frameworks — principally the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) — to explain why students adopt generative AI tools such as ChatGPT. Using PLS-SEM on a sample of 503 Polish university students, Strzelecki (2023) found habit and performance expectancy to be the strongest predictors of behavioral intention to use ChatGPT, which in turn was the strongest predictor of actual use behavior. Related studies extend this framework with perceived knowledge and trust (Amin, Kim, & Noh, 2024), age, gender, and experience as moderators (Arthur, Salifu, & Abam Nortey, 2024), an integration of TAM with social cognitive theory (Awal & Haque, 2024), and adoption-related anxiety across countries (Budhathoki, Zirar, Njoya, & Timsina, 2024). More broadly, systematic reviews of AI in online higher education find that empirical research on AI adoption has grown rapidly but remains fragmented across theoretical frameworks and outcome measures (Ouyang, Zheng, & Jiao, 2022).

AI engagement, perceived performance, and screen-time growth

Evidence on whether AI tool use improves academic or work performance is decidedly mixed. On one side, a meta-analysis of 65 independent studies found generative AI use associated with a medium-sized improvement in college students' academic achievement (Hedges' g = 0.53; Sun & Zhou, 2024), a bibliometric review documents rapidly expanding positive coverage of generative AI's educational potential (Bahroun, Anane, Ahmed, & Zacca, 2023), and students themselves report largely favorable perceptions of GenAI's benefits for learning (Chan & Hu, 2023). On the other side, a large field experiment with high-school math students found that unrestricted access to GPT-4 significantly improved practice-session performance but led students to perform worse on unaided exams once access was removed — evidence that AI can function as a learning "crutch" without adequate safeguards (Bastani et al., 2025) — and a systematic review concludes that over-reliance on AI dialogue systems is associated with measurable

declines in students' independent cognitive performance (Zhai, Wibowo, & Li, 2024). Adoption surveys likewise note that most students report using AI primarily for convenience-oriented tasks such as summarizing or drafting rather than deep learning (Ovi, Fierro, & Smith, 2025), and reviews of GenAI-based assessment call for research designs sensitive to this benefit/over-reliance tension (Xia, Weng, Ouyang, Lin, & Chiu, 2024). Dwivedi et al. (2023) frame this as an open, multidisciplinary question with implications for research, practice, and policy rather than a settled empirical matter.

H3: AI tool engagement is positively associated with perceived improvement in academic or work performance.

Separately from how often or how long someone uses AI tools, the breadth of purposes for which they use them (study help, work productivity, coding, writing, entertainment) may itself be associated with perceived benefit, on the logic that more versatile use reflects deeper integration of the tool into one's workflow — consistent with adoption research showing that behavioral intention and habitual use, not raw frequency alone, drive perceived value from AI tools (Strzelecki, 2023; Amin et al., 2024).

H4: Breadth of AI tool use purposes is positively associated with perceived improvement in academic or work performance.

Finally, because AI tools are themselves accessed through smartphones and laptops, heavier AI engagement could plausibly add to — rather than substitute for — overall device use, showing up as self-reported growth in combined screen time relative to the previous year. This would be consistent with adoption research documenting extremely rapid growth in AI tool use among students in the last two years (Contractor & Reyes, 2025).

H5: AI tool engagement is positively associated with self-reported growth in combined screen time.

III. RESEARCH METHODOLOGY

From the literature review, we understood that AI has become an integral part of human beings, now the present study wants to understand is the usage of AI is same in students and working professions and also is there any advantage of AI usage for working professionals when compared to the students. The study also focuses on improvement of productivity with the help of AI usage. Data were collected through a self-administered online survey (17 items) distributed to a convenience sample of college students and working professionals. Forty-five complete responses were analyzed (N = 45). Respondents were predominantly aged 22–25 (71.1%), male (62.2%), and full-time students (55.6%); the remainder were working professionals (24.4%), students with part-time jobs (15.6%), or other (4.4%). ChatGPT was the most-used AI tool (71.1%), followed by Gemini (15.6%) and Claude (11.1%). Table 1 displays the demographic profile of the sample.

Table 1
Sample characteristics (N = 45)

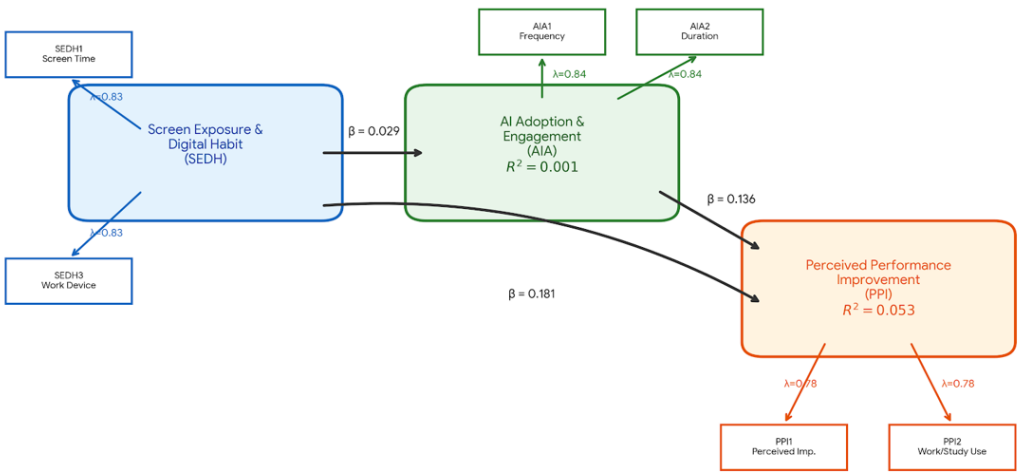
Characteristic	Category	Number of respondents	Percentage
Age group	18–21	8	17.8
	22–25	32	71.1
	26–30	4	8.9
	30+	1	2.2
Gender	Male	28	62.2
	Female	17	37.8
Occupation	Full-time student	25	55.6
	Working professional	11	24.4
	Student + part-time job	7	15.6
	Other	2	4.4
Primary AI tool used	ChatGPT	32	71.1
	Gemini	7	15.6
	Claude	5	11.1
	Other	1	2.2

Source: Authors compilation

IV. ANALYSIS AND DISCUSSION

On the 4-point screen time scale (1 = 2–4 hours, 4 = 8+ hours), the mean was 2.60 (SD = 1.14); 33.3% of respondents reported 8+ hours of combined daily screen time. AI use frequency (1 = rarely, 4 = daily) had a mean of 3.53 (SD = 0.79), with 66.7% reporting daily use. Daily AI use duration (1 = under 15 minutes, 5 = 2+ hours) had a mean of 2.89 (SD = 1.40). Perceived performance impact (1 = not sure, 3 = yes, significantly) had a mean of 2.58 (SD = 0.58), with 62.2% reporting a significant perceived improvement. Screen-time growth (1 = decreased, 3 = increased) had a mean of 2.53 (SD = 0.73), with 66.7% reporting increased screen time relative to a year earlier.

Figure 1
Model showing the impact of AI in perceived performance



Source: Authors compilation

Table 2
Construct correlation matrix

	ST	DUB	AIE	AIP	PPI	SCU
ST	1.000	0.073	-0.003	0.192	0.082	0.209
DUB	0.073	1.000	0.048	0.282	0.137	0.082
AIE	-0.003	0.048	1.000	0.468	0.217	0.074
AIP	0.192	0.282	0.468	1.000	0.011	0.136
PPI	0.082	0.137	0.217	0.011	1.000	0.061
SCU	0.209	0.082	0.074	0.136	0.061	1.000

Source: Authors compilation

It is found that there is a clear evidence that working professionals are using more AI than full-time students with p level 0.046, and working professionals have 70.0% screen time, but only 33.3% of working professionals with screen time of AI.
We also observed that there is a significant increase in the screen time usage from the past screen time, with a p value of 0.012, for this Fishers exact test has been used and the respondents who have mentioned the option as Neutral has been excluded who are just 2 in the sample.
Surprisingly both the groups have mentioned that their performance is increasing with the usage of AI, though the usage of full-time students are less, and in this case we failed to reject the Null Hypothesis

V. CONCLUSION

The present study explored the relationship between screen time, AI tool usage, and perceived academic and professional performance among students and working professionals. The findings indicate that AI applications have rapidly become integrated into everyday academic and workplace activities, with ChatGPT emerging as the most widely used generative AI platform among the respondents. A considerable proportion of participants reported daily AI usage, highlighting the increasing dependence on AI-assisted learning and productivity tools.
The descriptive analysis showed that nearly half of the respondents spend more than six hours per day using digital devices, while approximately two-thirds reported an increase in screen time compared with the previous year. Most respondents also perceived AI tools as contributing positively to their academic or professional productivity, suggesting that AI is increasingly viewed as a performance-enhancing technology rather than merely an information retrieval tool. Furthermore, the comparative analysis revealed that working professionals demonstrated significantly higher AI usage than full-time students, indicating that occupational demands may encourage more extensive adoption of AI technologies.
It is found that 46.7% of the respondents are spending more than 6 hours on the screens. 64.4% of the respondents told that there is a significant increase in the screen time from the last year, 62.2% of the respondents mentioned that Instagram is their entertainment platform. AI usage has become a daily activity with a 60% respondents and ChatGpt is used by majority of the respondents. Around 91% of the respondents have mentioned that there is some improvement in their work/productivity because of AI. To conclude the working professionals are using more AI than students and there is a positive impact of AI on the academic performance and professional performance.

VI. SCOPE FOR FURTHER RESEARCH

Future research should employ larger and more diverse samples, adopt longitudinal research designs, and incorporate objective measures of academic and workplace performance alongside self-reported perceptions. Additional variables such as AI literacy, digital competence, trust in AI, ethical concerns, and cognitive dependence could further enrich future models. Such investigations would provide a deeper understanding of how AI technologies influence learning, productivity, and digital behaviour in the evolving educational and professional landscape.

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