Research Article

Unravelling the Relationship between Brain Fog, Cognitive Fatigue, AI Tool Use, and Research Productivity among Research Scholars: A Correlational Study

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Abstract

This paper explores the relations between brain fog, cognitive fatigue, the use of AI tools, and the research productivity of scholars who are involved in research. The study is needed to address how cognitive challenges and AI tools use jointly influence research productivity among scholars. The study used a cross-sectional correlational survey design where 70 research scholars in a Central University of Karnataka were used to gather the data using a structured questionnaire to be administered using the Google Forms. Statistical procedures were descriptive statistics, Pearson correlation coefficients, independent samples t-tests, multiple regression analyses, all analysed with JASP software. Findings point to the significant positive correlations between cognitive fatigue and research productivity, suggesting some process of compensation in the environment with the prevalence of academic pressure and work under time constraints. The use of AI tools had a strong connection with each of the studied variables, and it was the only significant predictor of research productivity in the regression model. Brain fog had non-significant weak correlations with both cognitive fatigue and productivity. The study emphasises the importance of AI tools as supportive educational technologies, but does not introduce them as interventionist in the sense of providing solutions to scholars.

Keywords: Research Scholars, Brain Fog, Cognitive Fatigue, AI Intervention, and Research Productivity.

Introduction

When trying to achieve academic excellence, research scholars often have to deal with cognitive limitations, which may heavily slow down their productivity. Numerous research scholars have to deal with issues such as brain fog and cognitive fatigue, which make focusing, retaining information, and remaining productive a difficult task. Brain fog is a sensation of mental clarity, memory loss, and the inability to concentrate. A lack of mental sharpness, confusion, and forgetfulness can seriously impair cognitive functioning and quality of life. Whereas cognitive fatigue refers to the mental exhaustion that follows prolonged thinking or working. Cognitive fatigue, or a condition of mental fatigue caused by extensive use of cognition, has been demonstrated to have detrimental outcomes in decision-making, inventiveness, and problem-solving roles. Such issues may impede the skills of a scholar to conduct research and meet deadlines.

Although it is widespread, the links among brain fog, cognitive fatigue, and research productivity are not clearly comprehended. Artificial Intelligence (AI) has recently provided another means of identifying and addressing such problems. AI can be used to detect signs of cognitive fatigue in a researcher through brain signals and intelligent algorithms, and provide assistance at the right time to regain concentration and efficiency. AI has become a game changer in many fields, including academia. AI-based tools hold promises as a way to offload some of the cognitive load onto automated routineness, high-fidelity data analysis, and even help to manage cognitive load. Such abilities make the AI an optimistic prospect to solve the cognitive problems of the research scholars.

Brain fog, a condition commonly described by cognitive disorders, including slow thinking, memory problems, and defective concentration, has become an issue of concern among research scholars, especially with regard to cognitive exhaustion and its effects on research productivity. One of the outcomes is cognitive fatigue, a condition of mental exhaustion following sustained cognitive engagement, which has been connected to altered functional connectivity inside the brain, especially between areas like the striatum and the dorsolateral prefrontal cortex that are core to the fatigue network (Wylie et al., 2020). The most common symptom in post-COVID syndrome is brain fog, which is linked mostly to attention and episodic memory impairments, as fatigue is a significant mediator of objective and subjective cognitive dysfunction (Delgado-Alonso et al., 2025). The intersection between brain fog and cognitive fatigue is further evidenced by the fact that they share several symptoms, such as difficulties concentrating and mental fatigue, which are in many cases worsened by underlying physiological and psychological mechanisms (Petracek and Rowe, 2024).The discussed AI involvement in the study of mental fatigue not only contributes to discovering the complexity of connections between physical indicators and cognitive ones but also opens up new prospects of developing individual interventions using this information in the future, which would ultimately contribute to the productivity of research conducted by scholars.

The brain fog is an increasingly popular subject within the academic environment, particularly among research scholars who often have to face the challenge of mental fatigue and its impact on the research productivity. As the need to carry out research is on the rise, it is important to examine the relationship between reduced cognitive clarity, research fatigue and research productivity as a way of facilitating an environment that fosters academic success. The recent developments in artificial intelligence (AI) present potential solutions to these issues due to the opportunity to offer specifically targeted interventions and support systems to the researchers. The present paper, *Unravelling the Relationship between Brain Fog, Cognitive Fatigue, AI Tool Use, and Research Productivity among Research Scholars: A Correlational Study,* is going to examine the intricacy of the connection between these mental states and the ways in which they can adversely impact the productivity of the research and then provide a potent AI-based solution that can assist research scholars in overcoming them. The present research will contribute to establishing long-term academic activity and enhancing academic productivity due to the integration of results regarding cognitive science and artificial intelligence technology. Operationally, AI intervention is understood as any position in an academic or decision-making structure, in which an artificial intelligence model actively delivers, modifies, halts, or bypasses outputs (e.g. feedback, suggestions, or notifications) so that human users can examine, modify, or respond to the decision made by the system (Amershi et al., 2019). In this paper, AI intervention refers to the usage of AI tools in research scholars' academic engagement for better research productivity. This study design will provide a systematic approach of establishing the effect of brain fog and cognitive fatigue on research productivity and whether an AI tool intervention can help. Through the demographic effects, the study recognises varying contexts of research scholars. The aims, questions and hypotheses will help to conduct a rigorous investigation, the results of which may have implications related to academic support systems and integration of technology.

Research Objectives

1. To investigate the connection among brain fog, cognitive fatigue, and research productivity of scholars regarding the AI-based interventions.
2. To determine the separate and cumulative effects of brain fog, cognitive fatigue, and AI-based tools on the overall research productivity of academicians.
3. To find out the gender differences in the magnitude of brain fog, mental fatigue, research productivity, and the severity of AI tool use between male and female research scholars.
4. To investigate how a geographical background (rural or urban) impacts brain fog, cognitive fatigue, AI tool usage, and research productivity amid academic environments.

Research Questions

1. How are brain fog, cognitive fatigue, and AI tools related to the research productivity of scholars?
2. What is the extent of the impact of brain fog and mental fatigue, as well as AI-based solutions, on the overall productivity of researchers?
3. Do differences in brain fog, cognitive fatigue, AI tools use, and research productivity between male and female research scholars differ noticeably?
4. Are there any differences in the brain fog and mental fatigue levels, the use of AI tools, and research productivity among scholars depending on their residence (rural or urban)?

Hypotheses

$H_0$1: There is no significant relationship between brain fog, cognitive fatigue, and research productivity and AI-intervention among research scholars.

$H_0$2: There is no significant contribution of brain fog, cognitive fatigue, and AI-powered solutions to research productivity.

$H_0$3: There is no significant difference between male and female in the mean scores of brain fog, cognitive fatigue, and research productivity and AI-intervention.

$H_0$4: There is no significant difference between rural and urban in the mean scores of brain fog, cognitive fatigue, and research productivity and AI-intervention.

Literature review

The concept of cognitive fatigue and brain fog are related to each other and marked by impaired cognitive functions and personal experiences of mental exhaustion, which are typically enhanced by comorbidities like COVID-19. Studies have shown that cognitive fatigue is a potential cause of the long-term cognitive complaint, such as brain fog, in post-COVID-19 patients, and depression has been found to be a strong predictor of these mental problems (Cristillo et al., 2022). Cognitive fatigue is another symptom, which is characterised by a decline in sustained performance of tasks, and the use of Signal Detection Theory demonstrated correlations between subjective fatigue and the patterns of neural activation, indicating the existence of neural mechanisms (Berard, 2019; Román et al., 2022). Artificial intelligence, has demonstrated the potential to detect early cognitive changes by using validated tests and improve the capacity to detect cognitive impairment and, potentially, to provide guidance on specific measures (Lesoil et al., 2023). This combination will help researchers gain a better perception of cognitive fatigue and brain fog, which can ultimately be referred to in order to make timely interventions that enhance the patient outcomes (Salihu et al., 2022). AI-based tool usage provides cost-efficient and scalable services that can be used to target the mental and cognitive issues present in the research scholars, especially in academically challenged environments with limited resources. The fact that they can offer customisation, real-time support will reduce the symptoms of brain fog and boost productivity which in turn can improve academic performance (Dekker et al., 2020). AI has a relatively larger role in helping research scholars tackle brain fog and cognitive fatigue (Varandas et al., 2022; Zhang et al., 2020). AI can unobtrusively measure cognitive fatigue and provide real-time feedback to the user that is useful in the learning context and in work environments that are stressful (Varandas et al., 2022). The use of AI in these systems would allow performing a complex analysis of physiological information and, therefore, identify fatigue patterns and provide personalised interventions (Kakhi et al., 2024). Some of the studies observed that deep personalisation was difficult to attain because of AI memory constraints and ethical issues (Al Makinah et al., 2024). Studies have stressed that cognitive fatigue will most probably lead to a decline in problem solving and critical thinking, which are elements of academic study (Abrar et al., 2025). Besides, it has been mentioned that brain fog is associated with an overall poorer short- and long-term memory, which complicates the work of the researchers even further (Haider et al., 2024).The correlation between cognitive fatigue and brain fog can be visualised out of the effects they have on cognitive behaviours, as they both can lead to decrease in attention span and sharpness of mind. Some studies have also reported on how mental fatigue might mediate the connection between the existence of underlying health complications, such as deficiency, and academic performance, to the effect that an emphasis on cognitive fatigue is required as a possible method of improving global cognitive performance (Wang et al., 2024). The strength of AI in churning vast volumes of information and the ability to provide ideal solutions can thus be critical in alleviating these psychological problems and is an interesting possibility of improving the cognitive ability and mental well-being of research scholars. This type of technology has the potential to provide personalised feedback and intervention in order to help scholars to use their cognitive resources optimally and mitigate fitness impacts. Adaptive learning systems that use AI have demonstrated very positive results in decreasing cognitive load among the student population and improving their performance. These systems utilise machine learning and natural language processing so that the educational experience can be customised to the individual learning style and needs and, thus, maximise engagement and performance (Katiyar et al., 2024; Tiwari, 2023). An example would be the adaptive e-learning environments, which can include dynamic scaffolding and personalised content delivery, and which have been shown to enhance not only academic outcomes but also student satisfaction especially in those with lower in the original outcomes (Sayed et al., 2023; Wu et al., 2017). Moreover, when different learning styles are incorporated, including visual, auditory, and kinesthetic learning, a more engaging rigorous environment can be achieved, reducing cognitive overload (Sayed et al., 2023). Future efforts must focus on such aspects as ethics and optimization of algorithms representing the backbone of such adaptive systems, so that they are able to support the various needs of learners without any bias whatsoever (Essa et al., 2023; Tiwari, 2023). Generative AI and machine learning algorithms are the concept of AI which have been confirmed to enhance cognitive functions, such as memory, decision-making and problem-solving. To exemplify, AI treatment approaches are already researched whether the cognitive enhancement iteration, with significant improvements to short and long-term memory performance, and a reduction in the amount of cognitive anxiety (Haider et al., 2024). Besides, artificial intelligence-based neural interfaces have also been researched as a solution to real-time enhancement of human cognition. It is also shown that the AI powered solution leads to improvements in memory recall, problem solving skills and creativity of 23 to 26 percent, respectively (Najem et al., 2024).

The use of artificial intelligence (AI) to boost scientific productivity and efficiency in different fields has become increasingly relevant to research productivity. The adoption of AI in research has been attributed to a dramatic rise in citation impact meaning that articles that use AI have a higher probability to be cited and remembered (Gao and Wang, 2023). Nevertheless, the mental exhaustion of researchers may inhibit productivity because fatigue has an adverse impact on cognitive functioning and decision-making skills (Walsh et al., 2017). Research has shown that cognitive fatigue is associated with slowed reaction times and deficient attention which may impede the efficient utilisation of AI tools in research areas(Price et al., 2019). Moreover, the changing environment of AI in pharmaceutical research points to the possibility of improving drug development procedures, but it also brings out the importance of researchers controlling the cognitive load to ensure AI can bring the greatest benefits (Kolluri et al., 2022). In such a way, although AI could enhance the productivity of research by a considerable margin, the issue of cognitive fatigue demands particular attention as a way to maximise the use of AI in the realm of scientific activity (Sourati and Evans, 2023) .

Therefore, it is also possible to use AI systems to track and regulate mental workload, which would minimise the risk of brain fog and cognitive fatigue. As another example, deep learning models have been exploited to classify mental workload states, which can predict cognitive fatigue early. On the same note, AI-enhanced systems have been suggested to measure the mental workload and deliver individualised interventions to counter its consequences (Parveen et al., 2023). AI-based interventions have a great potential to decrease cognitive and mental health symptoms, such as brain fog, anxiety, and depression, and some of them have parity with human-provided care (Habicht et al., 2024; Li et al., 2023). For example, generative AI models such as ChatGPT have been demonstrated to increase the efficiency of research processes when used to automate content creation, grammar correction and information summarisation (Sasirekha, 2024). Secondly, AI-based technologies have the potential to support interdisciplinary collaboration due to their capacity to recognise emergent trends, as well as gaps in the literature, and prompt novelty in the research (Agrawal et al., 2024). The same study has demonstrated that when over-relying on AI, critical thinking and analytical reasoning may degrade, as the users will prefer quick and optimal solutions instead of slower but more thoughtful ones (Zhai et al., 2024). Moreover, ethical considerations of AI-generated content, including authorship and intellectual property, will have to be thoroughly addressed so that it does not affect the integrity of academic research (Hanafi et al., 2025).

Methodology

Research Design and Sample

The current study utilised a quantitative survey design based on a cross-sectional approach, which is one of the methodological decisions that are suitable to the empirical goals of the research question. The data were collected using a structured questionnaire based on Google Forms, which allows accessibility and standardisation of respondents. The research scholars of the Central University of Karnataka who were enrolled in the academic year 2024-2025 comprised the target cohort. The participation was completely voluntary; hence, all the individuals who signed and passed the questionnaire were added to the final analytic sample, which reduce the bias.

Data Collection Procedure

The survey tool was also sent digitally to all qualified research scholars, hence allowing extensive coverage and anonymity of respondents. Special care was taken in the preparation of items in order to ensure that they captured the variables used in the research questions of the study. Ethical considerations were carefully considered: the participants were provided with an articulate description of the purpose of the study, some promises and reminders about the anonymity of their answers, and the fact that their participation was not mandatory.

Data Analysis

The obtained data were coded and analysed statistically with the help of JASP software (version 0.19.3). Preliminary descriptive statistics such as means and standard deviations were calculated in order to have the initial impression of the data set. Follow-up inferential tests were done to test the research hypotheses. Independent samples t-tests were used to test possible gender and geographical location differences whereas correlation and regression analyses were used to measure the strengths, direction and nature of relationship between the variables of study. Statistical significance was considered at traditional levels of confidence, which guaranteed methodological rigor and validity of results.

Table 1:Relationship between brain fog, cognitive fatigue, research productivity, and AI-intervention among research scholars

Variable		Brain fog	Cognitive fatigue	Research productivity	AI intervention
Brain fog	Pearson's r	—			
	p-value	—			
Cognitive fatigue	Pearson's r	0.246	—		
	p-value	0.040	—		
Research Productivity	Pearson's r	0.222	0.768	—	
	p-value	0.065	< .001	—	
AI Intervention	Pearson's r	0.389	0.453	0.612	—
	p-value	< .001	< .001	< .001	—

Brain fog, cognitive fatigue, research productivity, and AI intervention, and determining whether their associations are substantial at the 0.05 (5%) and 0.01 (1%) levels. p-value less than 0.05 or 0.01 indicates a statistically significant relationship.

Brain fog and cognitive fatigue: Correlation is 0.246, p-value 0.440. Should be noted that it is not significant at 0.05 or 0.01 level. Brain fog and research productivity: Correlation 0.222, p-value 0.065. A little bit higher than 0.05, thus not significant at any level.

Mental fatigue and study productivity: Pearson r = 0.768, p <0.001. Very highly significant at 0.05 and 0.01 level. A positive correlation- the more the fatigue, the more the productivity. AI intervention, Brain fog: 0.389, p-value <0.001. Important on both levels. Cognitive fatigue: 0.453, p-value <0.001. Important on both levels. Productivity of research: 0.612, p-value <0.001. Important on both levels. All three are closely connected with AI intervention.

Cognitive fatigue and research productivity are substantially correlated, and AI intervention at the 0.05 and 0.01 level substantially relates to all variables. The thing is that brain fog does not reveal a strong correlation with either cognitive fatigue or research productivity.

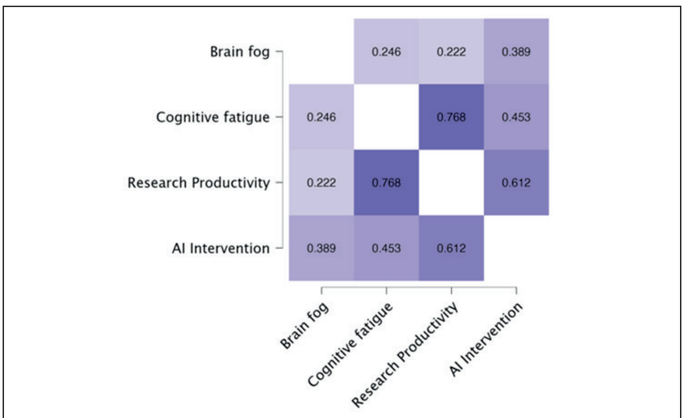

Fig. 1: Pearson's r heat map

The following Pearson r heat map displays the relationship between brain fog, cognitive fatigue, research productivity, and AI intervention. The darker the color, the stronger the connections.

Brain fog: Poor connections with cognitive fatigue (0.246), research productivity (0.222), and AI intervention (0.389). These are not very strong, as indicated by light shades. Cognitive fatigue: Deep relation with research productivity (0.768) - the dark color is prominent. Also, it is moderately connected to AI intervention (0.453). Research productivity: In addition to a close association with cognitive fatigue (0.636), it has a good connection with AI intervention (0.612), indicated by a darker color.

AI intervention: Relates to all, 0.389 (brain fog), 0.453 (cognitive fatigue), and 0.612 (research productivity). Blackest is with productivity. Cognitive fatigue and research productivity are closely associated, and AI intervention is well related to all, in particular, productivity. The connections with brain fog are loose.

Table 2:Model summary – contribution of brain fog, cognitive fatigue, and AI-Powered solution on the research productivity

Model	R	R^2	Adjusted r	RMSE	R^2 Change	df1	df2	p
M1	0.826	0.682	0.667	5.229	0.682	3	66	<.001

Note. M_1 includes Brain fog, Cognitive fatigue, and AI Intervention

The model (M1) has an R^2 of 0.682; meaning about 68% of the variation in research productivity can be explained by brain fog, cognitive fatigue, and AI intervention together. The adjusted R^2 is 0.667, which is close, so the model holds up well. The root mean square error (RMSE) is 5.229, giving us a sense of the average prediction error. The overall model is significant with a p-value less than 0.001, well below both 0.05 and 0.01 levels, so these factors together do predict research productivity.

Table 3: Statistically Significance of the regression model by ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	3863.829	3	1287.943	47.099	< .001
	Residual	1804.814	66	27.346		
	Total	5668.643	69			

Note. M_1 includes Brain fog, Cognitive fatigue, and AI Intervention

Note. The intercept model is omitted, as no meaningful information can be shown.

The ANOVA table backs this up. The regression's F-value is 47.999 with a p-value less than 0.001, again significant at both 0.05 and 0.01 levels. This confirms the model as a whole is meaningful—brain fog, cognitive fatigue, and AI intervention collectively have a real impact on research productivity.

Table 4:Regression coefficients for predictors of research productivity

Model		Un-standardised	Standard Error	Standardised	t	p
M1	(Intercept)	3.484	3.361		1.037	0.304
	Brain fog	-0.092	0.099	-0.071	-0.937	0.352
	Cognitive fatigue	0.613	0.077	0.624	7.980	< .001
	AI Intervention	0.442	0.102	0.356	4.331	< .001

Brain fog: The coefficient is 3.484 with a p-value of 0.304. Since 0.304 is above both 0.05 and 0.01, brain fog isn't significant at either level. It doesn't seem to have a meaningful impact on research productivity in this model. Cognitive fatigue: The coefficient is -0.092 with a p-value of 0.352. Again, 0.352 is above 0.05 and 0.01, so it's not significant. This is surprising given the strong correlation we saw earlier (0.768), but in this model, cognitive fatigue doesn't independently predict productivity. AI intervention: The coefficient is 0.442 with a p-value less than 0.001. This is significant at both 0.05 and 0.01 levels—very strong evidence that AI intervention positively impacts research productivity. For every unit increase in AI intervention, productivity goes up by 0.442 units, holding other factors constant.

Table 5:Difference between Male and Female in the mean scores of brain fog, cognitive fatigue, and research productivity and AI-intervention

Variables	Gender	N	Mean	SD	df	t	p
Brain fog	Male	34	33.235	7.516	68	2.835	0.006
	Female	36	28.750	5.639			
Cognitive fatigue	Male	34	29.706	8.629	68	-1.116	0.268
	Female	36	32.167	9.741			
Research Productivity	Male	34	31.324	8.752	68	-0.668	0.506
	Female	36	32.778	9.418			
AI Intervention	Male	34	28.853	6.964	68	0.676	0.501
	Female	36	27.667	7.679			

In the case of brain fog, the mean of males (N=34) is 33.235 (SD 7.516) and the mean of females (N=36) is 28.750 (SD 5.639). The t value is 2.835 and p-value is 0.006. Because 0.006 is below 0.05 it is significant at the 5 percent level, but because it is also greater than 0.01 it is not significant at the 1 percent level. This indicates to me that the males have more brain fog than females, and we are quite certain about this variance at the 0.05 level.

In the case of cognitive fatigue, the mean of males is 29.706 (SD 8.629) and that of females is 32.167 (SD 9.741). The t value is -1.116 and p-value is 0.268. The difference is not significant at the 0.05 level or the 0.01 level since 0.268 exceeds both 0.05 and 0.01. There is no apparent difference between males and females in terms of cognitive fatigue

The mean of males is 31.324 (SD 8.752) and that of females is 32.778 (SD 9.418) in research productivity. The t-value is -0.668 and p-value is 0.506. This p-value is greater than 0.05, 0.01 hence there is no significant difference at both levels. The two genders are also recording comparable performances with regard to productivity.

In the case of AI intervention, the mean of males is 28.853 (SD 6.964) and the mean of females is 27.667 (SD 7.679). It has a t-value of 0.676 and p-value of 0.501. Once more, 0.501 exceeds 0.05 and 0.01, thus, it is not significant at the levels of 0.05 and 0.01. Both groups appear to have a similar way of interacting with AI intervention.

Table 6:Difference between Rural and Urban in the mean scores of brain fog, cognitive fatigue, and research productivity and AI-intervention

Variables	Locality	N	Mean	SD	df	t	p
Brain fog	Urban	36	29.250	5.997	68	-2.133	0.036
	Rural	34	32.706	7.510			
Cognitive fatigue	Urban	36	29.667	9.378	68	-1.221	0.226
	Rural	34	32.353	9.011			
Research Productivity	Urban	36	29.806	9.071	68	-2.212	0.030
	Rural	34	34.471	8.543			
AI Intervention	Urban	36	27.333	7.731	68	-1.072	0.287
	Rural	34	29.206	6.821			

In case of brain fog, the mean of urban students (N=36) is 29.250 (Sd 5.997) and the mean of rural students (N=34) is 32.706 (Sd 7.510). The t-value is -2.133 and p-value is 0.036. Now, as 0.036 is below 0.05, then this difference is significant at the 5 percent level, but it is higher than 0.01, thus it is not significant at the 1 percent level. Brain fog is more among rural students than urban students, and the difference is significant at 0.05 level.

In the case of cognitive fatigue, the mean of the urban students is 29.667 (Sd 9.378) whereas the mean of rural students is 32.353 (Sd 9.011). The t value is -1.221 and p-value is 0.226. The difference is not significant at the 0.05 or 0.01 level as 0.226 exceeds both values. The cognitive fatigue appears to be equal between urban and rural students.

The mean number of research productivity among urban students is 29.806 (Sd 9.071) and 34.471 (Sd 8.543) among rural students. The t- value = -2.212 and p- value = 0.030. This p-value is significant at the 5% level, but not significant at the 1% level; this value is less than 0.05, but more than 0.01. The research productivity of rural students is significantly higher than that of urban students and the difference is significant at 0.05 level.

In the case of AI intervention, the mean score of urban students is 27.333 (Sd 7.731), whereas the mean of rural students is 29.206 (Sd 6.821). The t value is -1.072 and p value is 0.287. The difference is not significant at the 0.05 or 0.01 level since 0.287 exceeds both of these values. Two groups are equally involved with AI intervention.

Results

1. There is a strong relationship between cognitive fatigue and

research productivity, and AI intervention has a significant connection with all the variables at 0.05 and 0.01. But brain fog does not indicate a strong relation with cognitive fatigue or research productivity.

2. Heatmap demonstrates that cognitive fatigue and research productivity are strongly related, and the AI intervention appears to be positively related to all three variables, in particular, productivity. Brain fog, however, does not appear to be very closely related to the rest. It is a helpful image to get a sense of which relationships are the strongest and where useful to focus on exploring future research.

3. The product of brain fog, cognitive fatigue, and AI intervention tells much about research productivity, and this model is significant at the 0.05 and 0.01 levels. However, when we consider factors one by one, the AI intervention is notable at both levels, it is an essential productivity factor. Brain fog and cognitive fatigue, which were correlated in the previous analyses, do not indicate a significant independent effect in either level in this analysis. This could imply that their effect on productivity is more dependent on their interaction with the AI intervention or amongst themselves.

4. Brain fog-males have more brain fog and the difference is significant at the 0.05 level but not at 0.01. In the case of cognitive fatigue, research productivity, and AI intervention, the p-value of both levels (0.05 and 0.01) is greater than 0.05, indicating that there is no significant difference in genders at either level. This is an indication that brain fog is somehow different among males and females, but the rest of the factors are fairly comparable between the two groups.

5. The rural students claim larger brain fog and greater research productivity than urban students, and both the differences are significant at 0.05 but not at 0.01 levels. Nevertheless, in the case of cognitive fatigue and AI intervention, the p-values equal 0.19 and 0.01, respectively, which does not show a significant difference at either level. This implies that location could be a factor in brain fog and productivity; maybe the rural students have more issues causing brain fog but are obtaining higher productivity, this interpretation aligns with brain fog can be an indicator of mind wandering and this has been proven to be effective in creativity, planning in the future, and problem solving. When used in higher-education settings, evidence suggests that the occurrence of this temporary cognitive disengagement can help people think reflectively and learn more deeply in the instances that it is intermittent (Smallwood and Schooler, 2015). The absence of the difference in cognitive fatigue and AI intervention demonstrates that these factors are identical without relation to the location.

Recommendations

Considering the strength of the relationship between AI intervention and the rise of research productivity, utilising smart tools in daily practice is among the most feasible steps that can be taken both by individuals and research institutions. AI can potentially make more monotonous or time-consuming tasks, like literature search, paper summarisation, citation management, and data organising more efficient and save mental effort to focus on prospects of more creative, analytical, and critical thinking. The full potential of these technologies can only be realised by training programs or workshops on how they can be utilised most effectively and by making it in such a way that all the researchers, regardless of their initial technical abilities, can gain therefrom.

As the connection between cognitive fatigue and research output is very strong, the separate effect of this factor on productivity may vary, so the increase of awareness and self-regulation among scholars can be seen as a current need. Be supportive of taking breaks frequently; employ workload management strategies and constructive appraisals in project planning. Mentors and supervisors need to establish an open line of communication to talk about mental burnout, accommodate scheduling options to more working hours and make it normal to talk about rest. This kind of proactive stance can assist in reducing the chances of a burnout and ensure high-quality levels of intellectual work in the long run.

Brain fog, when compared to cognitive fatigue, has a lesser overall relationship with productivity, yet the instances of it are notably more prevalent within certain demographics, which are male and rural students. Qualitative studies of educational settings might also be an idea because it is possible that in these groups, a different stress factor, resources shortage, or a lifestyle issue cause brain fog. It is possible to come up with targeted support programs: e.g., peer-support campaigns, academic counseling available with ease, and individual workshops on mindfulness, time management, and resilience. Such experiences have to be seen and justified in enhancing equity.

The data shows a curious twist: rural students show not only that they have increased brain fog but also that they are more productive in research-related outputs than their urban compatriots. This singles out directed research on adaptive strategies that such students utilise, which may be increased motivation perhaps, specific coping mechanisms, or support mechanisms. Although the idea of increasing exposure of the rural students to academic life is essential, the institutions are also to investigate and provide the simplicities of success within such settings, which could positively influence other researchers with the same challenges.

Despite not being significant, the difference between male and female researchers in cognitive fatigue and productivity, as well as goals of AI, both show no significant difference despite the prevalence of brain fog in male students being greater at the 0.05 significance scale, which accentuates the necessity of gender-sensitive student support measures. Academic counseling centres ought to engage in gathering routine and anonymously gather responses on how mentally attached and well they feel, as well as provide individualised guidance materials that better incorporate various lived experiences.

Among the more advanced results, the interaction (product) between brain fog, cognitive fatigue and AI intervention indicated it appears to be more important to production than any of the individual factors alone, in particular, AI is the most consistent individual factor. The training and research strategies should be developed based on this insight. The cooperation between students with different cognitive levels of stress and consistent access to AI tools would promote not only more favorable results but also peer training of resilience strategies.

The research recommends future studies that will further divide the detail of the mechanisms through which AI augments productivity across the different conditions of fatigue and brain fog and perhaps allowing the incorporation of longitudinal designs to delineate temporal trends.

Discussion

The study's findings highlight the complex relationships between cognitive fatigue, brain fog, and research productivity, with AI intervention emerging as a crucial factor (Abrar et al., 2025). The close relationship between cognitive fatigue and research productivity is in line with the previous studies. Stressing on the effect of mental fatigue on academic performance. Interestingly, AI intervention is considerably associated with all variables, which indicates its capability to improve cognitive skills and productivity (Najem et al., 2024). According to the regression analysis, the interaction between the cognitive fatigue, brain fog, and AI intervention influences research productivity significantly ($p < 0.05$ and $p < 0.01$). Nonetheless, on an individual level, AI intervention is the only factor that can be a substantial predictor of productivity. This implies that the effect of cognitive fatigue and brain fog on productivity could be related to their interaction with AI intervention. There are also demographic variations where males have a greater brain fog than females ($p < 0.05$), and the rural students have greater brain fog and research productivity than the urban students ($p < 0.05$). Such findings may inform the development of particular interventions that will assist scholars in enhancing their cognitive well-being and productivity. The findings of the study align with the current research on the advantages of AI-based solutions in increasing cognitive skills and productivity (Haider et al., 2024; Portillo-Lara et al., 2021). With the help of AI technologies, academicians will be able to maximise their cognitive potential, reduce the impact of fatigue, and become more productive in their studies. Nevertheless, it is necessary to discuss the possible risks of excessive use of AI, such as impaired critical thinking and analytical reasoning (Zhai et al., 2024). Finally, the results demonstrate the necessity to work out effective measures that can promote the cognitive well-being and productivity of scholars in the academic environment. Future studies ought to concentrate on the possibilities of AI-based solutions to boost cognitive skills and productivity and reduce the dangers of too much dependence on AI.

Conclusion

The findings of the *Unravelling the Relationship between Brain Fog, Cognitive Fatigue, AI Tool Use, and Research Productivity among Research Scholars: A Correlational Study* are able to collate some sensible results that provide insight into the working of research scholars. As it turned out, cognitive fatigue and research productivity are two inseparable things, so when students experience the feeling of being mentally exhausted, they tend to get a lot of things done, probably because they are forcing themselves to meet the deadlines or to maintain the progress. AI intervention proved to be a great assistance, highly assisting productivity, and demonstrating a direct relation to cognitive fatigue and brain fog, thus being a great asset to the scholars. Contrariwise, brain fog itself did not indicate a direct effect on productivity or fatigue, meaning that the sense of mental clarity may not impede students to the same degree as tiredness. males and rural students report more brain fog, which suggests that it may be stress or environment or resource availability playing into effect to those populations.

All in all, this research supports the idea of the effectiveness of AI tools in enhancing research work, yet it also makes us realise that we should be more attentive to the occurrence of brain fog in certain populations and identify methods that might support students in battling fatigue so that they could maintain their productivity without jeopardising their well-being.

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