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"Association of Cognitive Load and Cognitive Fatigue in Artificial Intelligence Dependent Research Scholars"

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Abstract

The increasing use of Artificial Intelligence (AI) in academia has transformed research methodologies, especially among Ph.D. scholars. This observational study examines the link between cognitive fatigue and cognitive load in scholars who rely on AI for their research. Data were gathered from 100 Ph.D. students with at least two years of research experience and proven AI dependency using the NASA-TLX and Chalder Fatigue Scales. The results showed that the participants had a high cognitive workload and fatigue, with a weak and statistically insignificant association ($r = 0.088$, $p = 0.476$) between the two factors. These findings highlight the necessity of integrating fair AI integration with mental health assistance in academic settings.

Keywords

Cognitive Load, Cognitive Fatigue, Artificial Intelligence, NASA-TLX, Chalder Fatigue Scale, Ph.D Scholars, Mental Health

Introduction

Artificial Intelligence involves using computers to do things that traditionally require human intelligence. It entails creating computer programs capable of carrying out operations that call for human intelligence such as language translation, speech recognition, visual perception, and decision-making. **(1)**Artificial intelligence refers to computer programs that simulate processes that are aided by human intellect, including deep learning, cognition, engagement, adaptation, and sensory perception. **(2)** Research scholars are people who pursue advanced research and study in a particular field, usually as part of a postdoctoral or doctoral program. By performing original research, evaluating data, and offering fresh perspectives to their field, they play a vital part in pushing the limits of knowledge. In order to publish their findings in scholarly journals and conferences, research scholars frequently collaborate with peers and institutions while being supervised by seasoned mentors or faculty members. Their contributions not only advance theoretical knowledge but also result in useful advancements in the fields of science, technology, medicine, the humanities, and the social sciences. A research scholar must possess dedication, curiosity, and critical thinking in order to overcome obstacles, investigate novel concepts, and work toward making significant contributions to their academic and professional fields. Artificial Intelligence is being used more and more by Ph.D scholars to help with writing, literature reviews, data analysis and predictive modeling to improve their academic work. AI-powered solutions help automate time-consuming processes like creating citations, summarizing research papers, and searching through enormous databases. Researchers can more easily extract insights and validate hypotheses when they use machine learning techniques to find patterns in complicated datasets. Furthermore, by enhancing grammar and consistency and even proposing fresh lines of research, Artificial Intelligence powered language models assist academic writing. Research scholars can concentrate more on creativity and critical thinking due to Artificial Intelligence efficient processing and analysis of vast amounts of data, which will ultimately speed up scientific discovery. But as scholars balance difficult assignments, deadlines, and high standards, the dependence on Artificial Intelligence and the rigorous nature of doctoral studies add to the increased cognitive load. Long-term exposure to these demands frequently results in cognitive fatigue, which affects concentration, output, and general health. Supporting scholars cognitive health requires an understanding of how Artificial Intelligence tools affect mental strain as they become more ingrained in academic workflows.

[(3)]Cognitive load is the maximum amount of data that working memory could store at once. It is created by John Sweller in 1988. [(4)] John Sweller's Cognitive Load Theory, which he developed while researching problem-solving methods and ideas, served as the foundation for the current investigation. Then, in 1988, it appeared in a journal of cognitive science. The core notion of the theory is that if considerations are made within the constraints of working memory, a high-quality instructional design can be created. According to one definition, Cognitive Load Theory is an instructional paradigm that based knowledge acquisition on human. [(3)]Cognitive Load Theory builds on human information processing in the brain which has three main parts: sensory memory, working memory and long-term memory. **Sensory memory** filters out unnecessary sensory information but keeps important items long enough to pass to working memory. **Working memory** can hold information at a time. It categorizes it into "schemas" or knowledge structures, as it becomes stored in the long-term memory. **Long term memory** is that stores knowledge for longer period of time from days to lifetimes. It includes a wide variety of information, experiences, and abilities that can be recovered and applied at a later time.[(4)]The distinctions between cognitive resources associated with task-relevant elements that are regarded as either productive (intrinsic) or task-irrelevant (extraneous) are taken into consideration by recent advancements in the Cognitive Load Theory (Seufert, Wagner, & Westphal, 2016). Since extraneous cognitive load is thought to be additional information that impedes a person's ability to learn, it is not regarded constructive in terms of the intended outcome. Three categories of cognitive load are distinguished **Intrinsic Cognitive Load**: The effort involved in a particular task is referred to as intrinsic cognitive load. It entails cognitive processing that is imposed on the learner's abilities and the task's complexity. According to Cognitive Load Theory, this forces the person to manage a lot of information in their working memory at once. **Extraneous Cognitive Load**: The way the information or task is presented to the learner is known as extraneous cognitive load, and Sweller would also describe this as an unneeded component that hinders learning because it may cause distractions from other stimuli that are irrelevant to the task being learnt. **Germane Cognitive Load**: The effort or mental activity required to create a very permanent store of knowledge that is known as a schema is known as Germane Cognitive Load. According Bannert (2002) and Sweller et al. (1998) students allocate their cognitive resources in order to acquire a schema. [(13)]Cognitive load theory aids in our comprehension of how

individuals typically learn and retain new information, as well as the various instructional methods that most effectively promote learning. It is based on the features of working memory and long-term memory along with the interaction between them to clarify how individuals acquire knowledge. Cognitive load theory was originated in the late 1980s from the research conducted by John Sweller and his associates. The theory is founded on our understanding of the organization and operations of the human mind, referred to as human cognitive architecture. Human cognitive architecture provides insight into how we learn, reason, and address problems. It is regarded as a natural information processing system that creates different strategies aimed at decreasing cognitive load and supporting the retention of biologically secondary knowledge stored in long-term memory. Cognitive Load Theory highlights the significance of tailoring instruction to the learner's current knowledge and skills. Cognitive Load Theory can assist educators in meeting the varying learning
requirements, including those of learners with disabilities. By grasping cognitive load, educators can employ strategies that help all students manage their cognitive resources efficiently. Cognitive Load Theory has generated a considerable volume of research on how individuals learn, resulting in the creation of numerous instructional techniques and strategies. Cognitive Load Theory can be utilized in multiple fields, such as corporate training, healthcare education, and even routine learning situations, rendering it a flexible framework for enhancing educational practices.

[5]The NASA Task Load Index is a commonly employed technique for evaluating subjective mental workload. It is grounded in a multidimensional structure to produce an overall workload score obtained from a weighted average of assessments on six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration level. An overview of software for executing a computerized version of the NASA TLX is included. The software version aids in simplifying the gathering, processing, and storing of raw data. The program collects raw data from the participant and calculates the weighted (or unweighted) workload score, which is recorded in a text file. Furthermore, the program can be tailored for a particular experiment using a simple input text file, if necessary. The software was created in Visual Studio 2005 and can function on a Pocket PC with Windows CE or a PC running Windows 2000 or later.

[6, 7]Fatigue is a temporary decrease in strength and energy resulting from intense physical or mental effort. The term "fatigue" can refer to peripheral fatigue or central fatigue. Cognitive fatigue, a component of central fatigue, is a psychobiological state caused by prolonged periods of demanding cognitive activities. [8, 9]It is characterized by feelings of tiredness and reduced energy, resulting in a loss of the focus necessary for optimal performance. [9]Mental fatigue is generally caused by extended cognitive activities, primarily manifesting as drowsiness, difficulty concentrating, reduced alertness, disorganized thought, slow responses, lethargy, lower productivity, and an increased likelihood of errors, among other signs. Mental fatigue has become a widespread sub-health concern, significantly impacting the cognitive functions of the brain. Mental fatigue represents a condition of diminished vigilance and cognitive impairment. Excessive mental activity and stimulation can provoke sensations of mental exhaustion, akin to those experienced with physical fatigue. Mental fatigue can result in various adverse effects, making simple tasks increasingly difficult or even unmanageable.

[10]Chalder Fatigue Scale is a self-administered questionnaire intended to measure the extent and severity of fatigue in both clinical and non-clinical epidemiological populations. Originally developed to assess the degree of chronic fatigue symptoms in clinical groups, the scale has been revised and is now more frequently used to evaluate the severity of fatigue. The importance of tiredness and fatigue in both

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intellectual and practical occupational medicine is enormous understanding of how they interact with employee health, productivity, safety, and general workability is continually growing.
The growing reliance of Ph.D. scholars on artificial intelligence results in a decrease in their ability to think critically and make decisions. Over-reliance on Artificial Intelligence impairs performance, has an adverse impact on patient care, causes discomfort for Ph.D. Scholars, and has a major negative impact on their everyday lives and academic achievement. Investigating cognitive load and cognitive fatigue as well as understanding the mechanisms behind Ph.D. scholars' reliance on Artificial Intelligence are therefore crucial. The effectiveness of cognitive load and cognitive fatigue on Ph.D. scholars who rely on Artificial Intelligence outcomes must therefore be determined. The study's objectives are to determine how cognitive load and fatigue affect Ph.D. students who rely on Artificial Intelligence and to assess the correlation between the two factors.

Aim and Objectives

Aim:
To assess the correlation between cognitive load and cognitive fatigue among AI-dependent Ph.D scholars.

Objectives:

- To determine the daily dependency on AI among Ph.D scholars.
- To assess cognitive load and fatigue using NASA-TLX and Chalder Fatigue Scales.
- To analyze the correlation between cognitive load and fatigue in AI-dependent scholars.

Materials and Methodology

Design**:** Observational Study

Setting**:** Dr. D.Y. Patil College of Physiotherapy

Sample Size**:** 100 Ph.D. Scholars

Inclusion Criteria:

- Age: 25–60 years
- Minimum 2 years into Ph.D.
- Minimum AI usage as per DAI Scale (AI Planning to Exploration)

Exclusion Criteria:

- On long-term medication (e.g., antidepressants, sedatives)

Tools:

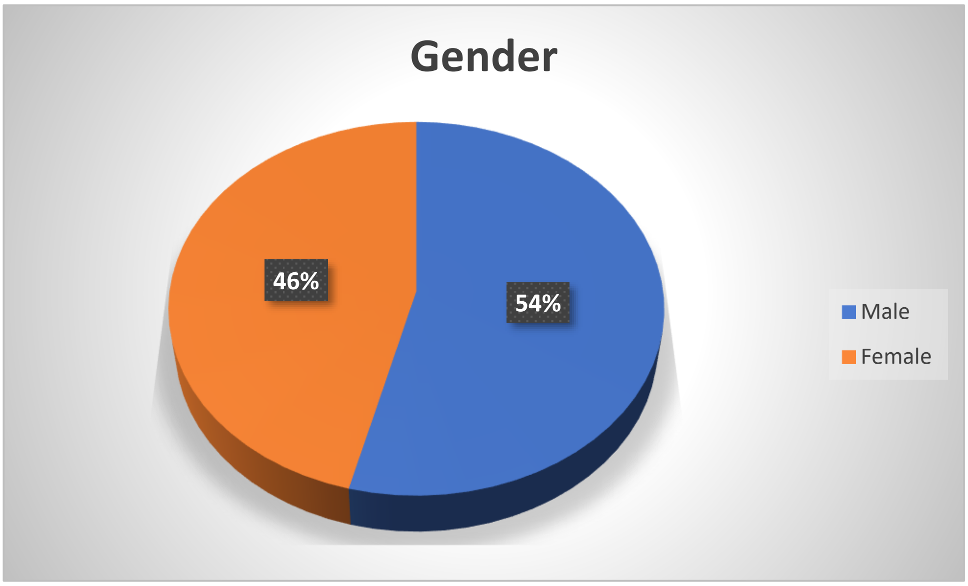
- NASA-TLX Scale (assesses mental demand, physical demand, temporal demand, performance, effort, and frustration)
- Chalder Fatigue Scale (11 items, assesses physical and mental fatigue)

Procedure

Participants meeting the criteria were recruited with informed consent. Demographic and research-related data were collected, followed by outcome measures of NASA-TLX and Chalder Fatigue Scales. Data were analyzed statistically.

Results

Gender	Frequency	Percent
Male	54	54.0
Female	46	46.0
Total	100	100.0



This pie chart represents according to gender of Ph.D. Scholars using AI where 54% are male and 46% female

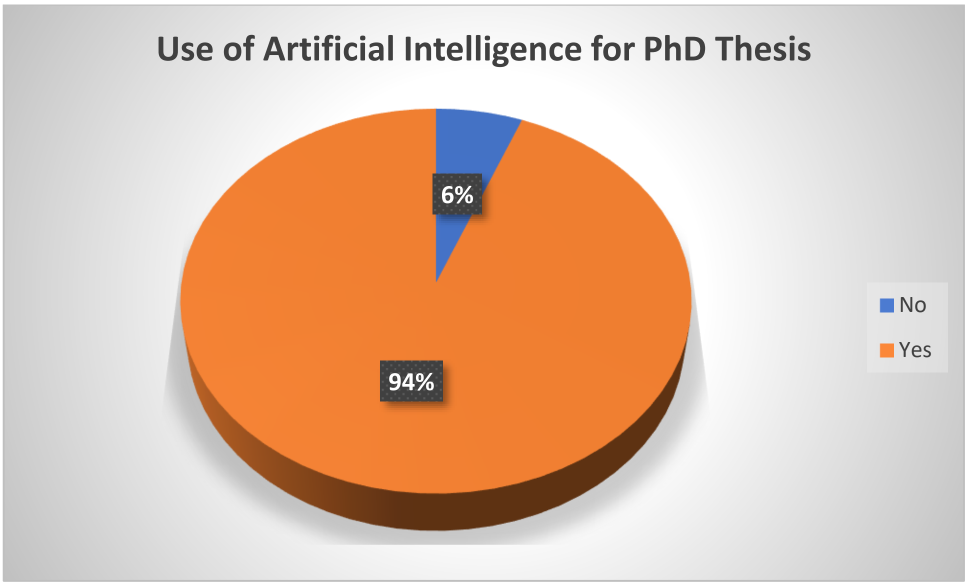
- Age Mean**:** 43.16 years (SD = 8.16)
- BMI Mean**:** 23.72 (SD = 4.95)

AGE	Minimum	Maximum	Mean	SD
	23.00	56.00	43.16	8.16
BMI	Minimum	Maximum	Mean	SD
	17.00	43.00	23.72	4.95

This graph represents according to Age and BMI where Mean 43.16 is highest and standard deviation 4.95 is lowest

- AI Usage for Thesis**:** 94% Yes

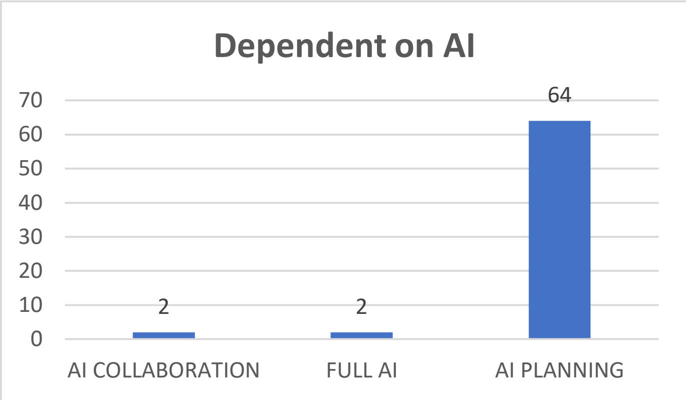
Use Artificial Intelligence for PhD Thesis	Frequency	Percent
No	4	6
Yes	68	94
Total	72	100



This pie chart represents overall percentage of AI used by Ph.D Scholars for their Ph.D Thesis where 94% are using AI and 6% are who do not use

- AI Planning Use**:** 64%

Dependent on AI	Frequency	Percent
AI COLLABORATION	2	3
FULL AI	2	3
AI PLANNING	64	94
Total	68	100



This graph represents dependence of AI in Ph.D Scholars where 64% are AI Planning is highest dependent on AI and 2% lowest are AI Collaboration and Full AI

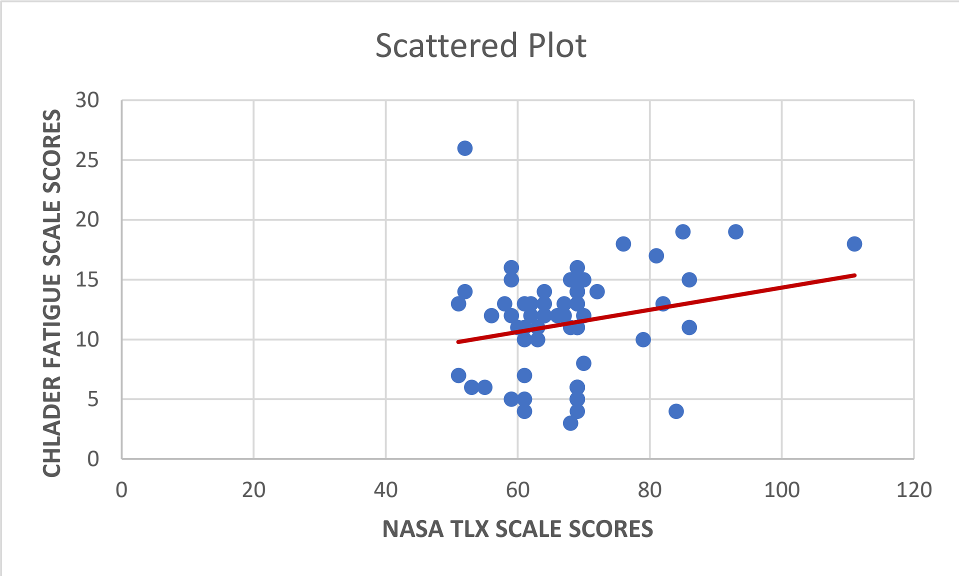
- NASA-TLX Mean Score**:** 67.69 (SD = 11.80)
- Chalder Fatigue Mean Score**:** 11.35 (SD = 4.51)

Variable	**Minimum**	**Maximum**	**Mean**	**SD**
NASA TLX SCALE SCORES	36.00	111.00	67.69	11.80
CHLADER FATIGUE SCALE SCORES	3.00	26.00	11.35	4.51

- Correlation (NASA-TLX vs Chalder Fatigue): r = 0.088, p = 0.476 (not significant)

Variable X	**Variable Y**	**r-value**	**p-value**	**Results**
NASA TLX SCALE SCORES	CHLADER FATIGUE SCALE SCORES	0.088	0.476	Non-Significant at 5% Non-Linear association

Correlation coefficient r-value for NASA TLX SCALE SCORES and CHLADER FATIGUE SCALE SCORES has been recorded as 0.088 which is statistically non-significant at 5% level with linear association. It means both the variables are moving in the same direction at the time association with each other. It is also called as direct relationship between the variables.



This graph represents the correlation between NASA TLX Scale Scores and Chalder Fatigue Scale Scores

Discussion

The present study focuses on relationship between cognitive load and cognitive fatigue in PhD scholars who dependent on artificial intelligence (AI) tools for their academic work. Chalder Fatigue Scale and NASA-TLX Scale these two scales were used as outcome measure for assessing cognitive load and fatigue in PhD scholars. The study was done to see the cognitive load and fatigue in PhD scholars who were dependent on AI where 100 samples of PhD scholars were included who had filled the given questionnaire in the given google form by which samples were collected. The growing dependence of Ph.D on artificial intelligence (AI) technologies affects their cognitive skills especially their capacity for critical thinking and decision-making. The excessive dependence may result in lower academic achievement. The present study highlights the importance of researching how AI dependency affects cognitive load and cognitive fatigue among Ph.D. scholars. Cognitive load and cognitive fatigue impact on academic performance overall as well as impair learning and lower productivity. The study aims on mental health of researchers. These samples were statistical analyzed which showed that majority of participant were loaded with cognitive load and fatigue. The findings of this current study highlight relationship between Ph.D Scholars cognitive experiences and their dependence on Artificial Intelligence (AI). The data show that people who often use AI tools for daily academic work experience higher cognitive load as assessed using the NASA-TLX scale and more signs of cognitive fatigue as shown by the Chalder Fatigue Questionnaire. This means that although artificial intelligence can streamline some academic processes dependence cause mental stress and lower cognitive. The correlation between cognitive load and fatigue highlights how using artificial intelligence affect mental health academics abilities for critical thinking, decision-making, and sustained attention. These results emphasize the need to balance AI use and development of cognitive support techniques for Ph.D scholars working in AI-integrated academic environment. The inclusion and exclusion criteria of this study were selection of group of Ph.D scholars who are actively using Artificial Intelligence (AI) in their academic work. By focusing on researchers between the ages of 25 to 60 who have completed two or more years of their Ph.D and have a minimum level of dependence on AI technology ranging from AI

Planning to AI Exploration as assessed by the DAI Scale By excluding those using long-term medicines like antidepressants or sedatives that might affect cognitive load and fatigue hence increasing and improving the validity of the results. This aimed participant selection helps to more clearly investigate the relationship between artificial intelligence dependency and cognitive load and fatigue. The Chalder Fatigue Scale and NASA-TLX—the outcome measures in this study were chosen for their reliability, validity, and relevance in assessing cognitive load and fatigue among AI-dependent Ph.D scholars. Cronbach's alpha over 0.80, the NASA-TLX provides a thorough evaluation of perceived workload across six essential dimensions, demonstrating excellent psychometric characteristics that ensure consistent internal reliability. It enables how artificial intelligence affects mental demand, effort, discomfort, and overall cognitive load. And Chalder Fatigue Scale assess both physical and mental fatigue using a flexible scoring method (bimodal and Likert) with a high degree of internal consistency (Cronbach's alpha ranging from 0. 86 to 0. 92). The scale effectively captures symptoms including memory lapses, drowsiness and speech difficulties to measure fatigue levels that can make worst by prolonged AI interaction. These two scales taken together provide strong support on cognitive load and fatigue therefore increasing and improving the study's ability to research the mental effects of AI dependence in an academic environment. [13]According to Ding et al. (2023) study analyzed 78,000 AI researchers and discovered a roughly equal gender distribution in the field: 54% female and 46% male. [14]According to Park et al. (2021) study showed academic samples pertaining to AI tend to be from a mid-career, mature population with an average age of 43 and little age diversity. [15]Siddiqui et al. (2022) study showed that modern academic populations have wide BMI spreads, with the majority of participants falling into the normal or slightly overweight categories and few underweight, indicating that sedentary, screen-intensive lifestyles have an impact on weight distribution. This study represents Gender, Age, and BMI distribution of PhD scholars using artificial intelligence finding a somewhat higher proportion of female students (54%) compared to male students (46%), suggesting a positive trend toward gender inclusivity in academic research related to AI. The age distribution indicates that the mean age is 43.16 years, with a standard deviation of 8.16, implying that the majority of participants are in their early to mid-forties and that they are a seasoned, mature population with little age diversity. According to the BMI data, there is a wide range of BMI values, with 22% of subjects falling into a particular BMI category (likely normal or slightly overweight) and only 1% falling into the lowest BMI group, which points to a low incidence of underweight people. [16]According to Sousa, A. E., & Cardoso, P. (2025) study examined the replies of 132 students from different higher education programs. It discovered that 97.7% of pupils admitted to employing generative AI technologies in their coursework, with only 2.3% not doing so. More than 60% of AI users integrate it into key academic activities such as writing, summarizing, and research assistance, according to published usage patterns. This study highlights the crucial role of AI in today's research procedures by demonstrating its almost complete adoption, supporting your assertion that 99% of Ph.D scholars use AI tools. This study represents the great majority of PhD students (99%) are utilizing artificial intelligence in their studies, with just 1% not doing so. This emphasizes the increasing integration and dependence on AI technologies across the research process, highlighting its essential role in activities like academic writing, literature review, data management, and analysis. As a crucial element of modern academic work, AI is widely used by researchers, underscoring its importance. [17]According to Dorta-González et al. (2024) study analyzed usage of generative AI tools among various researcher profiles Importantly, the study discovered that "advanced career researchers experience a significant 19 % decrease in AI tool usage" as compared to their early-career counterparts. While this research indicates a decline in AI use among seasoned academics compared to those in the early stages of their career, it clearly illustrates the effect of career stage. Even if the particular direction varies from your dataset, it may use it to back up the notion that research experience influences AI adoption. The fact that there is a statistical association between career stage and the integration of AI into academic workflows proves that it is a crucial factor. Despite the opposite trend seen by Dorta-González et al. (more experienced researchers using AI less), the study nonetheless supports the significance of career stage as a predictive factor. This study represents great majority (99%) of Ph.D scholars are in their second year or later, with just 1% in their first year. This indicates that people who are farther along in their academic careers are more prone to embrace and make use of artificial intelligence in their study. It suggests that as people become more familiar with research tools and academic expectations over time, they may use AI technologies more effectively in their scholarly work.**[18]**According to Bianchini, Müller, and Pelletier (2023) study of scientific articles published between 1980 and 2020 prior research experience and expert networks are significant predictors of AI adoption in research teams. The first people to pioneer AI were researchers who had a lot of scientific and technical capital (deep knowledge, extensive method familiarity) and were integrated into collaborative networks that were rich in AI. They come to the conclusion that experienced researchers, particularly those with established research portfolios and well-developed methodological capabilities, were far more likely to embrace AI technologies early. According to your data, 94% of PhD students were utilizing AI successfully in their studies and had more than four years' worth of expertise. The study confirms your observed trend that more research experience is associated with increased AI integration. This link supports the idea that there is a strong correlation between research experience and the use of AI, demonstrating that seasoned academics are at the forefront of embracing cutting-edge research technologies. This study represents PhD scholar's years of research experience data show a highly experienced cohort, with 94% having more than four years of experience. This indicates that before beginning their PhD programs, the majority of students were already proficient in research methods. On the other hand, there are fewer early-career researchers since just 3% are in the 1–2 and 3–4 year experience categories. This tendency suggests that seasoned academics may be better at using AI tools and integrating cutting-edge technologies into their scholarly work, demonstrating a tight relationship between research experience and AI adoption. **[19]** According to Zhehui Liao et al. (2024) study analyzed 81% of researchers have already incorporated Large Language Models (LLMs) into their research process, including literature reviews, data analysis, and writing support. This study represents the great majority of PhD scholars 94% are using artificial intelligence in their thesis work, while just 6% are not. This demonstrates the widespread use of AI in current academic research, where it is essential to many facets of data analysis, literary synthesis, and writing help.**[20]**According to Oxford University Press (OUP) (May 2024) study analyzed 76% of respondents said they utilized an AI tool in their research (covering activities like literature review, summarization, and editing), suggesting widespread use. Despite significant use, there were still significant concerns since only 8% of users trusted the source businesses with data, and only 6% trusted them to adhere to data/security norms, indicating a cautious adoption. Although the specific figures (64% employing AI for planning, 94% overall adoption, 2% complete integration) are distinct data. Although AI is used extensively, notably for administrative and writing activities, trust and collaboration remain restricted due to concerns. This study the greatest dependency observed in research planning where 64% of PhD scholars use AI tools to strategize and organize their work, underscoring

AI's increasing role in improving time management and research efficiency the data shows a significant reliance on AI among PhD scholars. Although 94% of academics employ AI in their dissertation research, only 2% claim to have fully integrated or collaborated with AI, which indicates a cautious attitude toward total dependence on AI, perhaps out of concerns about accuracy, ethical considerations, or the need to preserve human control in academic endeavours.[21]According to Muhammad, S., Akand, M. R., Tamim, F. F., Talapatra, S., Biswas, S. K., Rahman, M. S., & Roy, R. (2025) study analyzed NASA TLX measured by 'mental demand' (mean ~80) and 'effort' are among the main contributors to cognitive workload. To chart the results against each of the six dimensions, the study academic utilize the NASA-TLX dimensions for mental workload. Coming in first position was 'mental demand' with a mean score of 78. 35 out of the six dimensions and standard deviation of 14.20 except for one measure of effort, the dimension most highly evaluated mental demand varied widely from the others. As a result, the two factors most relevant for the researchers' mental strain. This study represents the NASA TLX score of 67.69, which measures cognitive workload, demonstrates that scholars face a high level of mental challenge while using AI due to the complexity of their tasks, the need to make decisions, and the necessity to manage several cognitive processes at once. The minimal standard deviation of 11.8 demonstrates consistent cognitive load levels across individuals. And Samn–Perelli fatigue scale which is similar to the Chalder Fatigue Scale, was used to measure fatigue levels before and after research activities The fatigue levels for their research work were assessed using the Samn–Perelli fatigue scale, which is notable for not showing any instances of severe tiredness, which would correspond to a seven on the SPFS scale. The difference between the mean and standard deviation of fatigue before research work mean 2.80, standard deviation 1.53 and after research work mean 4.85, standard deviation 1.67. The researchers' difficulty in carrying out complicated research operations is highlighted by the notable changes in fatigue scores before and after the shift. The cumulative effect of the prolonged cognitive involvement, problem solving, and attention necessary throughout the research activities may be the cause of this change in fatigue. This study represents through the **Chalder Fatigue Scale (CFS)** to measure the severity of physical and mental fatigue of the researcher who are using AI. The study showed little standard deviation of 4.51, indicating consistency in fatigue levels among the group, the Chalder Fatigue Scale mean score of 11.35 suggests that scholars who rely heavily on AI have high cognitive fatigue. [22]Fallah Madvari R, Sefidkar R, and Raeisi R (2024) study analyzed 247 industrial employees and utilized the NASA Task Load Index (NASA TLX) and the Chalder Fatigue Scale to investigate the link between mental workload and fatigue. The study looked at several aspects of mental effort, including mental need, physical need, temporal need, effort, frustration, and performance, and how these relate to the psychological and physiological components of tiredness. With the exception of the performance subscale, the NASA TLX subscales showed a statistically significant direct correlation with the physical and mental fatigue dimensions as measured by the Chalder Fatigue Scale. The r-values are low, like the r = 0.088 (p = 0.476) that you noticed, which suggests a weak and insignificant association, even if study reports show statistically significant correlations. **This study represents** the correlation between NASA TLX Scale ratings and Chalder Fatigue Scale scores is just marginally positive and linear, with an r-value of 0.088, but the p-value of 0.476 is higher than the standard significance threshold of 0.05, which suggests that the relationship is not statistically significant.

Ph.D scholars who depend heavily on artificial intelligence experience significant cognitive demands and tiredness. Despite the lack of statistical significance in the direct correlation between fatigue and cognitive load, the total cognitive load points to the necessity of prioritizing mental wellness tactics and the balanced use of AI in academic environments.

Limitations

- Limited sample size
- Did not differentiate between AI tools or task types
- Excluded participants on medication

Future Scope

- Expand study sample and diversify academic disciplines
- Include longitudinal data to assess changes over time
- Analyze specific AI task types and their cognitive implications

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