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Cognitive Load And AI Dependence: Moderating Role of Decision-Making Styles Among University Teachers

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Abstract

The paper examines the connection between AI Dependence and Cognitive Load in a group of teachers in the university, with decision-making styles (Intuitive and Rational) acting as moderators. The increasing use of technology in undertaking academic activities means that teachers are increasingly dependent on AI applications. The design employed was cross-sectional, and 240 university teachers in Rawalpindi and Islamabad were surveyed. The NASA Task Load Index, Dependence on AI Scale, and Decision Style Scale were used. Regression analysis shows that Cognitive Load has a significant positive impact on AI Dependence. In the case of decision-making styles, the Rational decision style had a negative correlation with AI Dependence, but the Intuitive style had a positive correlation. The moderation analysis demonstrated that the Intuitive decision-making style is a significant strengthener of the connection between the AI Dependence and Cognitive Load. The implications of these findings are practical in terms of comprehending the application of technology in the field of academics and cognitive load management among teachers.

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Introduction

University educators have to cope with numerous directions at one time, such as curriculum design, administrative work, and teaching, with high cognitive load (Yousef et al., 2015). The Cognitive Load Theory by Sweller (1988) highlights the constraint of mental resources under intrinsic and extraneous loading. As artificial intelligence (AI) is rapidly being integrated in the education sector, numerous educators rely on AI applications to aid the planning, decision-making, and content creation process. It has been revealed that such tools have the potential to decrease workload (Kaplan and Haenlein, 2018), though the studies have also found that over-reliance on AI can reduce the ability to make independent decisions (Lu et al., 2024).

There are two broad categories of the decision-style: intuitive and rational, and they determine the way in which the process of thinking of a person is carried out when he or she is under cognitive load (Hamilton et al., 2016). Rational decision makers make decisions step-by-step, as opposed to intuitive decision makers who use emotional hints and shortcuts. As recent research revealed, the intuitive type of decision makers tends to rely on AI- based tools due to time-saving intentions (Phillips et al., 2015), whereas the use of a rational style can make the process less inclined towards automation.

With the rise in AI use in academic contexts, it is important to know how cognitive load and decision-making styles influence the reliance of teachers on AI. The current research fills this gap as it focuses on the moderating effect of decision-making styles on the association between cognitive load and AI dependence**.**

The Current Research and Hypothesis.

The hypotheses were set as follows, based on the literature review:

H1: Cognitive load is a positive predictor of AI dependence in teachers at the university.

H2: The style of intuitive decision-making is positively correlated with dependence on AI.

H3: A rational decision-making style has negative predictors of AI dependence.

H4: Decision-making styles will moderate the connection between the cognitive load and AI dependence, such that:

H4a: Intuitive style enhances the positive interaction between cognitive load and AI dependence.

H4b: Rational style undermines the relationship between cognitive load and AI dependence.

Literature Review

Sweller (1988) gave Cognitive Load Theory, emphasizing the limitation of mental resources by extraneous and intrinsic loads. As we see teachers managing multiple things, including curriculum designs, administrative duties, and instructions under very high load (Yousef et al., 2015). With increased usage of AI and new innovative designs of Artificial Intelligence, many teachers use it to support their planning, decision support, and content generation. Research has shown that these tools lessen the workload (Kaplan & Haenlein, 2018), but with that, studies also show that these tools may cause excessive reliance and can decrease the individual's own independent decision-making capability (Lu et al., 2024).

Decision-making styles are broadly classified as intuitive and rational, and they influence how an individual's thinking process works under cognitive load (Hamilton et al., 2016). Intuitive decision makers rely on emotional hints and shortcuts, whereas the rational decision makers go with a step-by-step approach and process. Recent studies have shown that intuitive decision makers are more likely to depend on technology and AI-driven tools because of shortcuts and time-saving goals (Phillips et al., 2015). Whereas rational style may reduce the tendency toward automation.

Previous Studies generated links among decision-making, cognitive load, and the use of technology. Only a few related these interactions, and this study fills the gap by examining the moderating role of decision making between cognitive load and AI Dependence.

Explainable Artificial Intelligence (XAI) has become an important area to connect complex results from machine learning models with an understanding of them. While the goal of XAI is to enhance transparency, much of the attention is still on developers rather than the professionals using decision-support systems (Doshi-Velez & Kim, 2017). This disconnect often leads to end-users not using XAI because they think the explanations are either too complicated or not useful for their tasks, which makes it hard for them to make good and fast decisions (Miller, 2019). The mental strain from XAI explanations greatly affects user performance and how well decisions are made. According to Sweller (1988) cognitive load theory, explanations that require more mental effort can hurt performance by overloading the user's thinking ability. In crucial areas like healthcare, where decisions need to be made quickly, bad explanations can cause delays and mistakes (Carvalho et al., 2019).

The current study examined the relationship between AI dependence and psychosocial maturity by focusing on emotional regulation, social responsibility, and independence. The descriptive correlation design was employed using a self-report questionnaire. The descriptive portion enabled the finding of how students rely on AI, while the correlation examined the relationship between psychosocial maturity and AI dependence. The study demonstrated a weak correlation between the two variables. However, there existed limitations as data were collected from a single institute, explaining lower generalizability (Scott & Bruce, 1995)

Critical thinking skills are important to assess the competency of AI-related tools; thus, another study aimed to highlight the importance of inclusion of a balanced thinking approach in education programs so that individuals can access the credibility of vast and complex sources. Correlation and descriptive analysis were used; the results showed a positive correlation between the AI use and critical thinking towards the transformation of innovative learning (Shah & Asad, 2024).

AI-based decision making has shown its importance, especially after COVID-19; thus, a study demonstrated the use of machine learning in decision making involving a large data set. The findings highlighted the importance of flexible instructional approaches linked with AI design so that it can enhance decision-making of both students and teachers. This represents AI as an effective tool for decision-making if it is designed vigilantly. (Mehrabi, Morphew, Araabi, Memarian, & Memarian, 2024).

Frederick (2005) explores how cognitive ability, measured by the Cognitive Reflection Test (CRT), influences decision-making, particularly in areas like time and risk preferences. Higher CRT scores, indicating more reflective thinking, are linked to more rational decision- making.

These findings suggest that decision-making styles, shaped by cognitive ability, may affect how individuals handle cognitive load, which is relevant for understanding AI dependence. Reflective decision-makers may navigate AI systems more effectively, highlighting cognitive traits as key moderators in technology adoption.

Cognitive Load Theory (CLT) has become a key idea to understand how people deal with information during tasks, especially when they have to do many things at once. Sweller (1988) defined cognitive load as the mental effort involved in processing information and identified three types: intrinsic, extraneous, and germane. Multitasking, particularly in situations with complex tasks or large amounts of information, increases these cognitive loads. The relationship between cognitive load and multitasking has been explored in recent years, showing that multitasking raises cognitive load and can hurt task performance and efficiency.

Studies show that multitasking tends to increase cognitive load because it requires more mental resources to handle several tasks at once. In complex task environments or those needing deep information processing, higher cognitive load can lead to cognitive overload, making it harder to focus and finish tasks successfully (Hahn et al., 2018). Also, multitasking can interfere with how we feel, which makes the cognitive load experience more difficult. Feelings like stress or annoyance can make cognitive load seem heavier, making it tougher to deal with the tasks (Tice et al., 2019). Having good ways to manage cognitive load is key to lessening the bad impacts of multitasking. These ways include focusing on what needs to be done first, cutting down on distractions, and using tools or methods to make tasks easier. Technology tools have been helpful in easing cognitive load. For example, digital assistants, automatic scheduling systems, and smart devices can help reduce mental demands, letting people concentrate on more complicated or important tasks (Pashler et al., 2001).

AI is believed to be the tool having a role at employee's personal development as well as it has been seen that employees are enjoying the fast speed of AI tools but at the same time depending on it for every small task so based on self-regulation theory, the study evaluated the relationship between AI dependency and resilience with the mediating role of failure analysis and the moderating role of results oriented cultural perception. Survey design was used, and data were evaluated via SPSS.

Thus, the findings represented that: (1) AI dependence is negatively linked with employee resilience; (2) AI dependence is negatively associated with the ability to analyse failure; (3) Failure analysis mediates the negative relationship between AI dependence and employee resilience; and (4) A results-oriented culture perception intensifies the impact of AI dependence on employee resilience through failure analysis. (Lu, Li, & Lin, 2024).

Elbanna and Fadol (2016) contributed to the literature on decision-making styles by investigating the role of intuition in strategic decision-making, particularly in the context of Egypt. The primary aim is to explore how various factors, including firm-specific, decision-specific, and environmental variables, influence the use of intuition in organizational decision- making. Key findings suggest that decision-making styles, particularly intuitive processes, cannot be fully explained by a single theoretical perspective. The study shows that firm-specific characteristics have a greater impact on the use of intuition in strategic decisions compared to environmental factors, challenging previous assumptions that external variables, such as market competition, are more influential in developed economies. Additionally, the study reveals that political and environmental factors have a reduced impact on Egyptian firms due to high bureaucratic regulation, a contrast to the findings in more market-driven countries (Elbanna & Fadol, 2016). This study's approach fills a significant gap in the literature by using a multi-perspective framework to examine intuitive decision-making, emphasizing the importance of context specifically, non- Western settings like Egypt. By doing so, it advances our understanding of how decision-making styles, including intuition, are shaped by organizational and contextual factors, addressing the call for more context- rich research on decision-making in different cultural and economic environments.

Method

A cross-sectional survey design was used to collect data from university teachers. The sample was collected from 240 university teachers within Rawalpindi and Islamabad, which included 123 male and 117 female, whereas the age group range 28-60 years. Our inclusion criteria basically included 1 year of teaching experience and the regular use of AI in academic tasks.

The three instruments used were:

1. NASA Task Load Index (NASA-TLX): This assesses the workload in six domains. Cronbach's alpha = .70.
2. Decision Style Scale (DSS): This measures both rational decision making and intuitive decision making.
   Cronbach's alpha: Rational =.62, Intuitive = .83.
3. Dependence on AI Scale (DAI): This is a 5-item scale which assess the reliance on AI
   Cronbach's alpha = .87.

It should be noted that the Rational decision-making subscale showed relatively lower internal consistency ($\alpha = .62$), which is acknowledged as a limitation.

Procedure

After the research proposal was passed by the concerned institutions, the second step was to contact the individuals to participate in the research. Recruitment was done face to face and via the internet so that all participants could access it. The method was made inclusive and accommodating, with flexibility on how the participants would participate in the study.

Informed consent was a sensitive aspect before any data collection started. This permission was not only a formal necessity, but also a ethical requirement. All the participants were adequately informed about the aim of the study, the nature of participation, and any risks or benefits associated with participation. The informed consent form contained clear explanations of the purpose of the study, the methods that were going to be used, and the use of the data. Also, it described the right of the participant to confidentiality and privacy. This was essential because the research dealt with sensitive personal information that was to be safeguarded during the research.

One of the major issues in studies with human subjects is confidentiality. It was assured that the personal information and responses of the participants would remain completely confidential. This implied that their identities would not be disclosed in any report, presentation, or publication of academic work. Anonymization of all the collected data was done to ensure the privacy of individuals. Identifiable data was not present in the datasets during analysis, and this means that no person could be identified with his or her answers. Furthermore, all personal data was kept safe, and it was in accordance with the data protection laws and research ethics.

Participants were further made aware of their rights, especially the right to pull out of the study upon any occasion without negative repercussions. This would guarantee them that they could pull out at any point that they felt uncomfortable or that they just did not want to go on anymore. The right to withdraw is another essential element in promoting informed and voluntary involvement in research, which enables people to make decisions which are in their best interests.

The respondents were also requested to pose questions at any stage during the research process. They were informed that, in case they had any doubts, questions, or concerns about the research, they could contact the researcher directly. This contributed to the creation of an open line of communication that led to trust between the participants and the researcher. The ability to pose questions and get straight answers made the participants well-informed about their participation in the study.

In terms of data collection and analysis, SPSS 26 was employed, which is a powerful statistical analysis tool. The data were mainly analyzed by using multiple regression and moderation analysis. Multiple regression was utilized to test the correlations among variables, and the moderation analysis was used to determine whether some variables moderated or affected the correlations among the key variables. The selection of these statistical techniques is due to their strength and their capability to deal with complex data relations, where the reliability and validity of the results are guaranteed.

Besides these technical issues, the participants were assured that their answers would be utilized in an academic context only. This highlighted the fact that the study was aimed at producing knowledge, and without commercializing their data. They had been made to understand that their input would help in advancing academic knowledge, and they could rely on the credibility of the results of the study. This openness made the participants feel relaxed and assured to take part in the research, and this strengthens the ethics of the study.

In general, the procedure of informed consent, the guarantee of confidentiality, and the communication process with the participants were all extremely important factors that allowed for the upholding of the ethical principles of the research and, at the same time, guaranteed the integrity of the data gathered and analyzed.

Results

Table 1

Multiple Regression Predicting Net Cognitive Load from Dependence on AI, Rational Decision- Making Style, and Intuitive Decision-Making Style

Variables	**B**	**SE**	**T**	**p**	**95%*CI***
Constant	2.986	0.195	15.290	0.000	[2.601,3.371]
DAI	0.580	0.031	9.061	0.000	[0.218,0.340]
DSS_R	-0.027	0.030	-0.411	0.681	[-0.071,0.046]
DSS_I	0.293	0.035	4.145	0.000	[0.077,0.217]

Note: β = standardized regression coefficient**.** **p<0.00, SE= Standard Error, CI= Confidence Interval

Table 2

Moderation Analysis of Rational Decision-Making Styles in Relationship of Cognitive Load and Dependence on Artificial Intelligence. (N=240)

					95% CI	
B	**S.E**	**T**		**p**	**LL**	**UL**
Constant	-5.82	1.48	-3.92	.00	-8.74	-2.90
CL	2.23	.31	7.22	.00	1.62	2.84
DMS_R	1.92	.38	5.08	.00	1.18	2.67
CL*DMS_R	-.52	.08	-5.93	.00	-.69	-.35

Note: B=Moderation Coefficient, S. E= Standard Error, CI= Confidence Interval, LL=Lower Limit, UP= Upper Limit, n= Selective Sample

The output of the results revealed that Rational Decision-Making Styles statistically impact the relationship between Cognitive Load and Dependence on Artificial Intelligence. The moderation is shown by a significant interaction effect. And in this case, the interaction effect is significantly negative *(B= -.52), t= -5.93, p<0.01*. Further, the R^2 =.43, which depicts that the model explains 43% of the variance in the relationship, i.e.

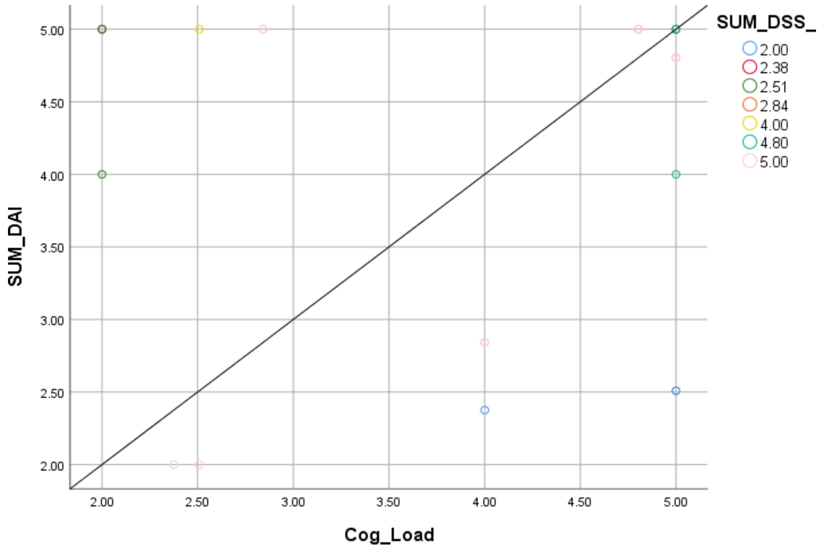

Figure 1: The moderating role of Rational Decision-Making Styles in the relationship of Cognitive Load and Artificial Intelligence (dependent variable) is 43%.

The result analysis, along with the graph (figure), further clarifies that the moderation is shown by a significant interaction effect.

The effect of Dependence on Artificial Intelligence decreases (dependent variable) significantly ($p<.01$) with the increase of rational decision-making styles (moderating variable). Hence, in this case, interaction is negatively significant *(B= -.52), t= -5.93, p<0.01*.

Multiple regression indicated that Cognitive Load ($B = .580$, $p < .001$) and intuitive style ($B = .293$, $P < .001$) were key predictors of AI Dependence, whereas rational decision making was not statistically significant. Moderation analysis showed that the decision-making styles have a great influence on the relationship between cognitive load and AI Dependence.

Discussion

The purpose of this paper was to explore the connection between cognitive load and AI dependency among university teachers as well as to explore the moderating role of decision-making styles on this connection. It examined the influence of higher cognitive load on the likelihood of teachers using AI tools and whether the decision-making styles (intuitive and rational) were related to this relationship. The results prove the hypotheses in multiple aspects, demonstrating complex dependencies among cognitive load, AI dependency, and decision-making styles.

AI Dependency and Cognitive Load.

The research affirmed Hypothesis 1 (H1), which hypothesized that teachers who have more cognitive load are more likely to use AI tools. Cognitive load is a term used by Sweller (1988), which is defined as the mental effort needed to process information and accomplish tasks. As a teacher, this load can be augmented by the complexity of lesson planning, grading, administrative tasks, and other cognitive loads on teachers. Results showed that when teachers are faced with increased cognitive load, they might resort to the use of AI tools to offload some of such pressures to enable them to automate activities that could include grading, designing lessons, or answering students. Although these tools are supposed to make the job easier, they may be counterproductive in causing cognitive overload when over-used.

AI devices are perceived to be effective substitutes for the human brain, which can lessen the amount of work. Nonetheless, the excessive use of the AI tools, which were evident in this study, may cause what Sweller (1988) called extraneous cognitive load, or mental effort in the form of distraction, not contributing to learning or task accomplishment. Recent research conducted by the author shows that regression analysis showed that active AI users among teachers result in an increase in cognitive load, which supports the theory that although AI is meant to ease cognitive load, its overuse or inefficient use results in increased mental load.

This observation leads to the ideas by Schreiber et al. (2024), who believe that excessive reliance on AI disrupts cognitive functions. The danger that was pointed out by Schreiber et al. is that letting AI handle the cognitive workload means that people will have an additional mental load when a person needs to process new or surprising information, or work on a more complex decision-making process that the AI is unable to process. Thus, although AI provides a respite in the short term, in the long run, it can add to the adverse effects on the mental performance of users who engage in excessive use of AI.

AI Dependency and Decision-Making Styles.

Hypothesis 2 (H2) assumed that intuitive decision-makers who value efficiency over detailed analysis are more dependent on AI. The results confirmed this hypothesis, showing that intuitive decision-makers are more inclined to use AI tools because they are willing to spend as little mental effort as possible. Intuitive decision-makers are also likely to make decisions in a short time, basing their decisions on gut feelings and emotions instead of analysis. This decision-making mode is linked to the tendency to choose quick solutions and efficiency, which can be easily offered by AI tools. AI tools satisfy this desire in a fast and effective decision-making process by automating repetitive tasks, thereby supporting the reliance of intuitive decision-makers on the technologies.

This connection between intuitive choices and AI addiction singles out an important element of human-computer interaction in the pedagogical context. Educators who act fast and follow their intuition will have higher chances of using AI tools that can facilitate faster decision-making, thus decreasing their cognitive load. Nevertheless, this reliance on AI tools, as this research hypothesizes, can cause a bigger cognitive burden in the long term, as intuitive decision-makers can become too dependent on AI solutions, and their capacity to process complex information independently diminishes.

AI Dependency and Rational Decision-Makers.

Hypothesis 3 (H3) looked at the influence of rational decision-makers, with the hypothesis that the rational decision-makers would exhibit a negative tendency with regard to AI dependency. The results partially confirmed this hypothesis, which showed that in regression analysis, rational decision-makers had a negative but insignificant tendency towards AI dependency. Rational decision-makers are characterized by their disposition towards structured and analytical methods of solving problems. They normally receive information methodically and rationally, basing their process on evidence and logical reasoning, as opposed to impulse or feeling.

The researchers concluded that, compared to irrational decision-makers, rational ones were less inclined to overuse AI tools, as the latter engage in the task at hand more profoundly and have a preference to approach issues systematically. This may be an indication that when making rational decisions, people may be more inclined to challenge AI-generated solutions and find other ways of solving a problem, instead of fully depending on AI. Nonetheless, the trend was also negative, but not statistically significant in the regression model, which means that rational decision-makers might become less reliant on AI, but their cognitive load might not decrease significantly as compared to intuitive decision-makers. The implication is that rational decision-makers can process information in a more structured and autonomous way, but the application of AI tools can also have an impact on their cognitive load, but in a less significant way compared with intuitive decision-makers.

Moderation Analysis: Decision-Making Styles.

Hypothesis 4 (H4) was based on the hypothesis that decision-making styles would moderate the relationship between cognitive load and AI dependency. The results clearly confirmed this hypothesis, with the moderation test indicating that the style of decision-making had a strong effect on the correlation between the cognitive load and AI dependency. In particular, among intuitive decision-makers, the cognitive load was significantly affected by the use of AI tools. However, in contrast, the effect of AI dependency on cognitive load was less significant among rational decision-makers. This finding indicates that intuitive decision-makers feel more attached to their cognitive load and their use of AI, probably because they are more inclined to use AI tools to be productive and comfortable, resulting in more cognitive load in the case of overuse.

The moderation effect draws a crucial difference in the effect of the various decision-making styles on the interaction of the individuals with the AI technologies. The AI application is more likely to reduce an immediate cognitive load by allowing quick solutions to problems, but it may eventually lead to a worsening of the mental load in the long term, with the help of intuitive decision-makers. Alternatively, rational decision-makers can also be more skeptical and cautious when using AI tools, thereby avoiding the over-cognitive load of over-relying on AI tools.

Conclusion

The study examined how cognitive load is correlated with AI dependence among university teachers, and the problem of decision-making styles moderate the correlation. The findings indicated that those university educators with increased cognitive load are more inclined toward relying on AI. The teachers whose decision-making style was intuitive were more dependent on AI, but those who depended on it were comparatively fewer in number than those whose style was rational. The institutions can contribute by providing training on cognitive load management and encouraging balanced use of AI. One of the limitations is the cross-sectional design that does not allow causal inferences to be made. Further studies are necessary on the longitudinal impacts and the incorporation of other factors, which include personality and digital literacy.

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