Research Journal of Psychology (RJP)
Online ISSN: 3006-7219
Print ISSN: 3006-7200
Volume 3, Number 3, 2025, Pages 26 – 35
Journal Home Page
https://ctrjournal.com/index.php/19/index

HEC Recognized Y-Category

Relationship between Cognitive Load and AI Dependence among University Teachers: Moderating role of Decision Making Styles

Qazi Abdullah[1], Hamna Rehman[2], Minahil Shehzad[3], Hira Attique[4] & Sidra Zaki[5]

[1]*BS Student, Department of Psychology, Air University, Islamabad, Pakistan, Email: 211393@students.au.edu.pk*
[2]*BS Student, Department of Psychology, Air University, Islamabad, Pakistan, Email: 211403@students.au.edu.pk*
[3]*BS Student, Department of Psychology, Air University, Islamabad, Pakistan, Email: 211383@students.au.edu.pk*
[4]*BS Student, Department of Psychology, Air University, Islamabad, Pakistan, Email: 201996@students.au.edu.pk*
[5]*Lecturer, Air University, Islamabad, Pakistan, Email: sidra.zaki@students.au.edu.pk*

ARTICLE INFO

Article History:

Received:	*May*	*16, 2025*
Revised:	*June*	*21, 2025*
Accepted:	*June*	*26, 2025*
Available Online:	*July*	*02, 2025*

Keywords:

Cognitive load, AI dependence, Decision making styles, educational psychology, intuitive decision making, rational thinking, cognitive load theory.

Corresponding Author:
Sidra Zaki
Email:
sidra.zaki@students.au.edu.pk

OPEN ACCESS

ABSTRACT

As the highly robust environment of higher education keeps progressing, university instructors face increasing cognitive imposition due to their multi-role task nature and growing integration of technology in learning. This study investigates the relationship between cognitive load, decision making styles (rational, intuitive) and dependence on artificial intelligence (Al) among university teachers. Data were collected from 240 faculty members of both public and private sector universities in Islamabad and Rawalpindi. A cross-sectional survey design was employed and the Cognitive Load Theory was implemented. Cognitive load (NASA-TLX), Al dependence, and decision-making styles (rational and intuitive) were assessed using standardized instruments. Results established a significant positive correlation between cognitive load, decision making styles and AI dependence. The findings highlight the need for proficient cognitive strategies and measured integration of Al in educational settings to prevent over-reliance and preserve critical thinking. This research contributes to the literature on educational psychology and technology integration and offers practical implications for policy makers and educators in curating focused interventions and training programs to enhance decision-making competence and manage cognitive demands in academic environments.

Introduction

Human beings are inherently social creatures, recognized as the most intelligent species. This elevated position in the ecological hierarchy brings with it a multitude of responsibilities, spanning from day-to-day tasks to educational and occupational responsibilities to the broader societal roles.

These responsibilities are not merely tasks to be accomplished but also shape the individual's identity and their contribution to society. As humans evolve, so do the expectations placed on them, and the complexity of these responsibilities increases. These societal roles that define and shape men and women's responsibilities and duties are influenced by culture, religion, and many other factors (Carter et al., 2009). Historically, men and women have navigated their roles as providers and caregivers, which have always been intertwined with their existence. From the dawn of humanity, the need to fulfill these responsibilities has necessitated a range of cognitive abilities, including problem-solving skills, emotional regulation, and decision-making capabilities (Goel, 2000). The mental agility required for daily functioning in these roles has always been significant, but as the world has progressed, these cognitive demands have only intensified. For example, providing for a family once meant acquiring food and shelter, but today it involves navigating complex financial systems, career pressures, and personal development goals. Similarly, caregiving roles, once focused on physical nurturing, now also require emotional intelligence, multitasking, and even digital literacy. Therefore, while these roles have always been central to human society, the cognitive load of fulfilling them has evolved and grown more demanding over time.

Additionally, changing gender role expectations have led to a redistribution of responsibilities, with men increasingly taking on caregiving roles and women balancing professional and domestic duties. This shift in roles has been influenced by global connectivity, where the world now functions as a digital "global village." The exchange of ideas, cultural values, and information is now instantaneous, contributing to the evolving nature of social roles and expectations. This changing paradigm has restructured the duties of both men and women across all domains; for instance, just as the duties of mothers have evolved, so have the responsibilities of daughters. These evolving roles demand constant adjustment and adaptation, leading to an increase in cognitive load. This evolution has compounded cognitive load, as individuals strive to meet the increasing expectations associated with these responsibilities, often leading to a higher risk of cognitive overload and mental fatigue (Starcke & Brand, 2012).

Cognitive load, which is defined as the total amount of mental effort used in working memory (Sweller, 1988), encompasses the cognitive demands placed on individuals as they manage and balance various tasks, responsibilities, and roles in their daily lives. As these demands increase, the mental resources available to an individual are stretched thinner, and if the cognitive load becomes too overwhelming, the individual is at a greater risk of experiencing exhaustion, both physically and mentally, as noted by Skulmowski & Rey (2017). This exhaustion not only manifests as mental fatigue but also leads to a decline in behavior and performance, such as decreased productivity, decision-making errors, and lower effectiveness in task completion (Marcora et al., 2009; Martin et al., 2018).

The complexity of these dynamics presents a window of vulnerability in individuals, due to which they often seek external solutions to manage their cognitive load. In earlier times, this external support often came from reliance on joint family systems, where responsibilities were shared among family members, and in educational settings, where tasks were designated by teachers to students or fellow colleagues however, over the last decade, as society evolved, this reliance shifted towards technology, which facilitated easier access to information and resources. The integration of technology into daily life has drastically altered how individuals manage their cognitive load, providing tools and platforms that simplify tasks and speed up processes. The use of technology relieved cognitive load from users relying on it for support (Oluwajana et al., 2021). Individuals now acquire information from various online platforms such as websites, forums, and databases and use it to arrive at conclusions quickly and efficiently.

More recently, the advent of artificial intelligence (AI) has further transformed this landscape, automating processes and analyzing data to alleviate cognitive burdens (De Bruyne et al., 2023). AI tools gather existing data from various internet sources such as databases, archives, websites, journals, and even books. They then manipulate the data and information in whatever way instructed by the user, providing tailored solutions to specific queries (A. Kaplan & Heinlein, 2018). The level of efficiency presented by AI tools is unmatched by any other existing technological tool. As individuals increasingly rely on AI tools to manage their cognitive load, a paradox emerges: while these tools help ease the mental burden by providing quick solutions, they may also lead to cognitive fragmentation. Rather than integrating information and processing it holistically, AI often breaks down tasks into smaller, more manageable pieces. This compartmentalization reduces the need for individuals to engage in deep, complex thinking, leading to fragmented decision making. Over time, this reliance on AI could inhibit the development of cohesive thought processes, as users become accustomed to relying on external systems to synthesize and analyze information (Schreiber et al., 2024). The convenience and efficiency provided by AI may, therefore, come at the cost of losing the ability to integrate knowledge in a meaningful way, which is crucial for critical thinking and creative problem solving.

Literature Review

The evolving integration of artificial intelligence into decision making processes has prompted considerable scholarly interest in the interrelations between cognitive load, AI dependence and decision-making styles. Research indicates that users' interaction with AI systems particularly chatbots significantly influences cognitive and emotional engagement. Wang (2024) employed Structural Equation Modeling to examine emotional dependence on AI chatbots revealing that users' sense of identification and perceived control are critical determinants of emotional attachment. This relationship is moderated by psychological distance; "friend" chatbots enhance identification and control when psychological proximity is high whereas "assistant" chatbots diminish these effects under conditions of greater psychological distance. These findings underscore the importance of AI system design in managing users' cognitive and affective responses thereby impacting cognitive load.

Complementing this Karny et al. (2024) explored the implications of AI dependence on autonomy and task performance through behavioral experiments involving a dynamic decision making AI game. Contrary to concerns about AI undermining intrinsic skills their results demonstrated that AI can enhance task efficiency without compromising user autonomy, suggesting that AI tools when appropriately implemented can alleviate cognitive load by providing effective feedback mechanisms.

Further insights are provided by Lu, Li, and Lin (2024), who applied self-regulation theory to investigate the relationship between AI dependence and employee resilience. Their survey based study found a negative association between AI dependence and both resilience and failure analysis capabilities. Notably failure analysis mediated this relationship, while a results oriented organizational culture intensified the adverse impact of AI dependence on resilience. These findings highlight the complex cognitive and psychological ramifications of AI reliance in workplace settings suggesting that excessive dependence may impair employees' adaptive capacities.

In the realm of machine learning interpretability, Fox (2024) emphasized the relevance of Cognitive Load Theory (CLT) in the design and user interaction with complex AI models. While interpretability techniques that aim to enhance transparency poorly constructed explanations risk increasing cognitive load and diminishing user comprehension and trust. Fox advocates for the integration of CLT principles in AI system development to optimize cognitive processing thereby improving user understanding and acceptance.

With respect to decision-making styles, Del Campo et al. (2016) demonstrated that individual differences significantly influence heuristic use and, by extension, AI reliance. Rational decision-makers tend to engage less with heuristics and AI recommendations whereas spontaneous decision-makers exhibit greater dependence. The influence of cultural context further modulates these tendencies, underscoring the multifaceted nature of AI dependence.

Dewberry et al. (2013b) further delineated the role of cognitive tendencies and personality traits in decision-making competence. Their findings suggest that while decision making styles predict performance, personality traits such as conscientiousness and emotional stability exert a more substantial influence shaping the degree of AI reliance for decision support. Orlandi and Pierce (2019) contributed to this discourse by examining the interplay between intuitive and analytical decision making styles within mobile technology environments. Their study revealed that both styles are integral to decision making with intuition dominating stable contexts and analytical processing becoming paramount under dynamic conditions. This dual-process framework informs the variability in AI dependence, contingent on users' cognitive styles and environmental demands.

Collectively, this body of research elucidates the complex relationships among cognitive load, AI dependence, and decision-making styles. AI can serve as a cognitive aid, reducing mental effort and enhancing decision performance; however, overdependence may engender negative emotional and cognitive outcomes, such as diminished resilience and heightened emotional attachment. Moreover, individual differences in decision making styles and personality traits significantly modulate users' interaction with AI systems. These insights emphasize the necessity for designing AI tools that effectively manage cognitive load, accommodate diverse decision making preferences and foster both performance and psychological wellbeing.

Significance of Study

The research has a significance to highlight that how high amount of cognitive load leads educational professors towards AI dependency. Moreover, when teachers overly rely on AI with limited critical thinking their decision making will suffer. When they become dependent on AI, consequences can be dangerous due to lower generalizability, uncertainty of results and coding errors. Here it is important to investigate the moderating role of different decision-making styles as a previously deployed studies investigated importance of rational decision making when interacting with modern technology. Educational professors are subjected to high amount of cognitive load due to multiple responsibilities within an educational sector.

Objectives

1. To investigate the relationship between cognitive load, decision making style and AI dependence among university teachers.
2. To examine the demographic differences among the study variables among university teachers.

Hypotheses

1. There will be positive correlation between cognitive load and AI dependency.
    (a) Intuitive decision making style will have a positive relationship with AI dependency
    (b) Rational decision making style will have a negative correlation with AI dependency

Method

Research Design and Sample

Cross-sectional survey method was used in the current research and Sample size was calculated during G power analysis. Purposive sampling technique was used. Data was collected from the teachers of Public and Private sector universities of Rawalpindi and Islamabad. Age range of participants is 25 years to 60 years.

Instruments

Demographic Sheet

The demographic sheet included questions about employment status, gender, age, birth order, level of education, area of expertise, no. of years of experience, level at which teaching is being delivered etc.

NASA Cognitive Load index

NASA Task Load Scale (Hart &Steve land, 2006) is a 20-point scale which assesses work load on individuals. It is a self-rating scale used to assess the perceived cognitive workload. It measures the workload in 6 dimensions i.e.; (1) physical demand of task (2) Mental demand (3) Individual's own performance (4) The amount of time pressure involved in completing the task, (5) individual's own effort and (6) frustration involved in completing the task (Hart,2006) Each dimension is rated on a scale ranging from 0 to 10. Scores from 0 to 3 indicates low cognitive load, 4 to 6 medium and 7 to 10 indicates high score. Overall workload score (OWS) is generated by NASA task load index with the average rating across these dimensions. Overall workload is calculated by calculating the average of individual ratings for extensive assessment of workload; however, each dimension of workload is weighted equally i.e.; 1 /6. The average Score between 0 to 9 represents low workload 50 to 79 show high task load whereas, 80 to 100 represents very high task load. Cronbach's alpha for the NASA-TLX typically ranges between 0.80 and 0.90. This indicates high internal consistency and reliability of the scale, 10 to 29 shows medium workload, 30 to 49 shows somewhat high score.

Decision style Scale

Decision style scale is a 10 item scale, developed by (Hamiltonetal., 2016) which is designed to assess the manner by which individuals make decisions according to their cognitive functioning. The scale has 2 sub scales i.e.; rational decision making and Intuitive decision making having Five items of each. 5-point rating is used in which response 1 indicates strongly disagree, ranging to 5 which strongly agree. Higher score for rational items indicates a more rational decision making style and lower score for rational items indicates a low rational decision making style, Similarly, higher score for intuitive items indicates a more intuitive decision making style and lower score for intuitive items indicates a low intuitive decision making style with Cronbach's alpha values of 0.83 for the Intuitive scale and 0.62 for the Rational scale.

Dependence on AI scale

Dependence on AI (Wilter.Cetal., 2024) is a 5 point Likert rating scale, having 5 items, that assesses the level of dependence in AI. This scale assesses the different levels of AI

Dependence such as, the feeling of anxiety when there is no availability of AI, and the fear that technological tools will replace human beings. On this scale, the options range from1 (Strongly disagree) to 5 (strongly agree). Minimum possible score is 5 whereas highest possible score is 25. High scores show more dependence on AI. Similarly, low score shows less Dependence on AI.

Their liability of the scale, measured by Cronbach's alpha is 0.87 indicating strong dependability and good internal consistency.

Results

Table 1:

Table showing mean differences of two genders males and females at net cognitive load, dependence on artificial intelligence, rational, and decision-making style intuitive.

	Male		Female				
Variables	**M**	**SD**	**M**	**SD**	**df**	**p**	**t**
CLP	4.60	.71	4.46	.83	238	.29	.91
DAI	3.97	1.62	3.63	1.74	238	.27	.97
DMSR	1.99	1.60	2.46	1.74	238	.13	-1.34
DMSI	4.06	1.89	3.96	1.42	238	.65	.24

Note: M = mean, SD = Standard Deviation, df = degree of freedom, p = level of significance t = T-test, CLP = Cognitive load of Participants, DAI = Dependence of Artificial Intelligence, DMSR = Decision Making Style Rational, DMSI = Decision Making Style Intuitive

An independent samples t-test was also used to assess gender differences in cognitive load, AI dependence, and decision-making styles. The results showed no statistically significant gender differences in any of the measured variables.

Table 2:

Table showing mean differences of two university sectors (public, private) at net cognitive load, dependence on artificial intelligence, rational, and decision-making style intuitive.

	Public		Private				
Scales	***M***	***SD***	***M***	***SD***	***Df***	***p***	***T***
CLP	4.56	0.711	4.64	0.74	238	0.41	0.90
DAI	3.98	1.60	4.18	1.47	238	0.07	1.00
DMSR	2.10	1.61	1.90	1.58	238	0.33	0.92
DMSI	3.95	1.52	4.17	1.51	238	0.40	1.09

Note: M = mean, SD = Standard Deviation, df = degree of freedom, p= level of significance t= T-test, CLP = Cognitive load of Participants, DAI = Dependence of Artificial Intelligence, DMSR = Decision Making Style Rational, DMSI = Decision Making Style Intuitive.

An independent samples t-test was conducted to examine differences in cognitive load, dependence on artificial intelligence, and decision-making styles among two university sectors. The results indicated no statistically significant differences between the private and public sector.

Table 3:

Descriptive statistics and correlation for Study Variables

Variables	***N***	***M***	***SD***	***1***	***2***	***3***	***4***
CL	240	4.59	.727	1	.51**	-.77**	.69**
DAI	240	3.93	1.635	.51**	1	-.59**	.48**
DMSR	240	2.04	1.619	-.77**	-.59**	1	-.73**
DMSI	240	4.05	1.848	.69**	.48**	-.73**	1

Note: M = mean, SD = standard deviation, n = sample size, CLP = Cognitive load of Participants, DAI = Dependence of Artificial Intelligence, DMSR = Decision Making Style Rational, DMSI = Decision Making Style Intuitive

The Pearson product-moment correlation coefficient (r) was computed to assess the relationship between cognitive load, dependence on artificial intelligence, and decision-making styles (rational and intuitive). The results revealed a significant positive correlation between cognitive load and AI dependence ($r = .51$, $p < .01$), and between cognitive load and intuitive decision-making ($r = .69$, $p < .01$). In contrast, cognitive load was significantly negatively correlated with rational decision-making

Discussion

This study explored the relationships between cognitive load, decision-making styles (intuitive and rational), and AI dependency among university teachers. The findings contribute to the broader understanding of how educators interact with AI tools in order to handle their regular tasks and routines.

The study hypothesized that positive correlation will be between cognitive load and AI dependency which was consistent with many previous studies. Asif et al. (2024) identified positive correlation between mental workload and AI usage thus many users find cognitive relief within technological sources. Similarly, Zhai and Li (2024) concluded that users rely on artificial intelligence to explore mental shortcuts to solve complex problems.

The study further hypothesized that a significant positive correlation was observed between intuitive decision-making and AI dependency, suggesting that educators who rely on instinctive and fast judgments are more inclined to accept AI suggestions. This finding aligns with Kahneman's (2011) System 1 thinking, where decisions are made quickly and automatically. The relationship is further supported by Cao and Huang (2022), who found that users who spent more time visually focusing on AI suggestions were more likely to agree with them. Their study emphasized that even when AI performance was inconsistent, intuitive users maintained reliance, especially under task difficulty, indicating that intuitive users may trust AI input more readily and act on it reflexively.

In contrast, rational decision-making showed a significant negative relationship with AI dependency, suggesting that those who favor deliberate, analytical reasoning are less likely to depend on AI tools. The similar findings were reported by Buçinca et al. (2021), who demonstrated that participants with higher motivation to engage in effortful thinking (Need for Cognition) were less prone to overreliance on AI and benefited more from cognitive-forcing interventions. Rational decision-makers, being more skeptical and critical of automated recommendations, may prioritize personal judgment and accountability. Similarly, the 2020 study "In AI We Trust?" showed that while people occasionally rate AI decisions on par with human experts, overall perceptions of fairness and risk are mixed and highly influenced by individual traits, rational users, in particular, may question the credibility and ethical implications of automated decisions in sensitive fields like education or law. These findings emphasize that rational thinkers require transparency, justification, and control before accepting AI support, making them less susceptible to automation bias.

Independent samples t-tests was run to check for differences in gender and it revealed no significant gender differences in cognitive load, AI dependency, or decision-making styles among university teachers. Results are consistent with many older studies reporting gender differences in technology adoption. For instance, Chen and Hwang (2022) found that boys and girls had no significant difference at cognitive load when interacting with AI based game systems. Similarly, when interacting with computer stimulation learning system there were no significant gender differences at the cognitive load (Kaheru & Kriek, 2016). Findra et al (2014) reported that personality traits influence an individual's decision making style rather than gender. At examining artificial intelligence dependence Kymäläinen, Elo, & Södervik (2024) revealed that while there were some small differences in basic stats among genders, but they were not statistically significant. Another study by Chen, Xue, Li, & Luo (2025) also observed no gender differences found in the impact of using AI for instrumental support. These findings support the present study by backing up the interpretation that gender may not be a significant factor in shaping cognitive load level, AI reliance, preferred decision making styles in academic context and suggests that AI reliance is becoming more gender neutral now.

Independent sample T test was further used to examine the difference between private and public sector teachers at cognitive load, AI dependency and decision making styles. The findings indicated that there is no significant difference among both groups. A study conducted at Sindh, Pakistan revealed that there are no significant differences at mental workload and performance among both public and private sector teachers however teacher's individual cognitive ability defined their cognitive load (Musa et al., 2024). It was further claimed that private and public sector teachers may report differences in terms of different dimensions of cognitive load but it does not impact net cognitive load (Akhtar et al., 2022). At examining decision making styles it was claimed that decision making styles adapted by both public and private practice are transformational and participative and have similarity (Valcke et al., 2016). Moreover, it was discussed that private sector employees had greater motivation than public sector but it did not create any statically significant difference at their decision making (Irum & Bajwa, 2020). Acceptance of AI at teaching is related with their individual attitude towards technology rather than sector in which they teach (Wang & Leu, 2021). Individual's anxiety enables them to adapt or restrict the use of AI irrespective of the sector where they work.

Findings explain that cognitive load, decision making styles and AI dependency are influenced primarily by individual traits rather than the sector in which they work. Organization's structure may enable individual to adapt towards organizational needs but they may perceive differently according to their unique personality dimensions. Moreover, AI usage, decision making style adaptation, and amount of cognitive load is becoming gender neutral as the society is progressing

Conclusion

This research investigates the relationship between cognitive load and how it effects the university teachers to rely on AI and how their decision making styles serves in this relationship. The results showed that university teachers who faced more cognitive load are more likely to depend on AI and while depending on their decision making styles. Teachers whose decisions are based on intuition are more likely to depend on AI whereas teachers who rely on proper thinking with logical reasoning are relatively less dependent on AI which shows that this thinking might help to protect against over dependence. These findings show that how AI tools while being helpful can also lessen the mental engagement of teachers with their tasks. With this Decision making styles also plays a very important role where teacher's personal thinking habits can influence the use of AI. As the use of AI is getting very common in educational institutes so it's very important to create a balance between using technology and thinking and decision making.

Implications

1. By reducing teachers cognitive load, we can actually improve the workflow and get better support systems. In this way they will manage the tasks effectively to avoid over reliance on AI.
2. By providing AI education to teachers will also help them to understand the proper use of AI and avoid over reliance.
3. By giving out space to teachers such as creative room will allow them to brainstorm and get to new innovative ideas rather than depending on AI.

Future Suggestions

1. Research can be conducted at other provinces of Pakistan for broader perspective
2. Experimental research can be conducted to identify situational aspects of AI dependence.
3. Research can be used to design an inventory related to teacher's attitude towards artificial Intelligence

References

1. Akhtar, S. N., Hashmi, M. A., & Naqvi, S. I. H. (2010). A comparative study of job satisfaction in public and private school teachers at secondary level. Procedia-Social and Behavioral Sciences, 2(2), 4222-4228.
2. Carter, M. J. (2014). Gender socialization and identity theory. *Social sciences*, *3*(2), 242-263.
3. Chen, B., Hwang, G. H., & Wang, S. H. (2021). Gender differences in cognitive load when applying game-based learning with intelligent robots. Educational Technology & Society, 24(3), 102-115.
4. Chen, B., Hwang, G. H., & Wang, S. H. (2021). Gender differences in cognitive load when applying game-based learning with intelligent robots. Educational Technology & Society, 24(3), 102-115.
5. De Bruyne, J., Cuypers, A., Dheu, O., Garsia, S., Palumbo, A., & Elbi, A. (2025). Briefs on Artificial Intelligence and Liability-Some Points of Attention and Future Perspectives
6. Del Campo, C., Pauser, S., Steiner, E., &Vetschera, R. (2016). Decision making styles and the use of heuristics in decision making. Journal of Business Economics, 86(4), 389– 412.
7. Dewberry, C., Juanchich, M., & Narendran, S. (2013). Decision-making competence in everyday life: The roles of general cognitive styles, decision-making styles and personality. Personality and Individual Differences, 55(7), 783–788.
8. Hamilton, K., Shih, S. I., & Mohammed, S. (2016). The development and validation of the rational and intuitive decision styles scale. *Journal of personality assessment*, *98*(5), 523-535.
9. Irum, U., Bajwa, R. S., & Khawar, R. (2020). Motivation and decision-making styles at work: A comparison of public private sector managerial positions. *Review of Education, Administration & Law*, *3*(1), 77-89.

10. Kaheru, S. J., & Kriek, J. (2016). The effect of computer simulations on acquisition of knowledge and cognitive load: A gender perspective. African Journal of Research in Mathematics, Science and Technology Education, 20(2), 67-79.
11. Kannengiesser, U., & Gero, J. S. (2019). Design thinking, fast and slow: A framework for Kahneman's dual-system theory in design. *Design Science*, *5*, e10.
12. Karny, S., Mayer, L. W., Ayoub, J., Song, M., Su, H., Tian, D., ... & Steyvers, M. (2024, June). Learning with AI Assistance: A Path to Better Task Performance or Dependence? In *Proceedings of the ACM Collective Intelligence Conference* (pp. 10-17).
13. Kusá, A., Danechová, Z., Findra, S., & Sabo, M. (2014). Gender differences in purchase decision-making styles. European Journal of Science and Theology, 10(5), 113-123.
14. Kymäläinen, H. R., von Cräutlein, M., Elo, K., Galambosi, S., Honkanen, A., Pietikäinen, J., & Södervik, I. (2024). Integrating Artificial Intelligence (AI) Literacy Into Curricula: The Case of Agricultural Sciences at the University of Helsinki.
15. Lu, R., Li, F., & Lin, Y. The Influence of Ai Dependence on Employee Resilience Based on Self-Regulation Theory. *Available at SSRN 5037573*.
16. Morales-García, W. C., Sairitupa-Sanchez, L. Z., Morales-García, S. B., & Morales-García, M. (2024, March). Development and validation of a scale for dependence on artificial intelligence in university students. In *Frontiers in Education* (Vol. 9, p. 1323898). Frontiers Media SA.
17. Orlandi, L. B., & Pierce, P. (2019). Analysis or intuition? Reframing the decision-making styles debate in technological settings. Management Decision, 58(1), 129– 145.
18. Schreiber, C., Abbad-Andaloussi, A., & Weber, B. (2024). On the cognitive and behavioral effects of abstraction and fragmentation in modularized process models. *Information Systems*, *125*, 102424.
19. Skulmowski, A., & Xu, K. M. (2022). Understanding cognitive load in digital and online learning: A new perspective on extraneous cognitive load. *Educational psychology review*, *34*(1), 171-196.
20. Starcke, K., & Brand, M. (2012). Decision making under stress: A selective review. *Neuroscience & Bio behavioral Reviews*, *36*(4), 1228 1248.
21. Stegehuis, F., & Bondarouk, T. (2024). Engagement with disruptive technology: do digital generations matter? In *Research Handbook on Human Resource Management and Disruptive Technologies* (pp. 207-223). Edward Elgar Publishing.
22. Sweller, J., Ayres, P., Kalyuga, S., Sweller, J., Ayres, P., &Kalyuga, S. (2011). Altering element interactivity and intrinsic cognitive load. *Cognitive load theory*, 203-218.
23. Wang, Y. (2024). Emotional Dependence Path of Artificial Intelligence Chatbot Based on Structural Equation Modelling. *Procedia Computer Science*, *247*, 1089-1094.
24. Wu, C. H., Zhao, Y. D., Yin, F. Q., Yi, Y., Geng, L., & Xu, X. (2024). Mental Fatigue and Sports Performance of Athletes: Theoretical Explanation, Influencing Factors, and Intervention Methods. *Behavioral Sciences*, *14*(12), 1125.