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The Mediating Role of Perceived Cognitive Load in the relationship between Artificial Intelligence Literacy and Artificial Intelligence Anxiety

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Abstract

The expansion of AI applications in higher education increases the need for students to be AI literate in order to understand and effectively use this technology. Lack of sufficient knowledge in this area can lead to anxiety, worry, and feelings of helplessness. In this regard, this study aims to examine the mediating role of Cognitive Load in the relationship between Artificial Intelligence Literacy and Artificial Intelligence Anxiety. The method of the current research was descriptive-correlation with emphasis on structural equation modelling. The statistical population of the research was all postgraduate students (٣٢٠) (master's and doctoral) of the Islamic Azad University, Kazerun Branch. Based on the Krejci and Morgan table, ١٧٥ people were selected as the statistical sample of the research using simple random sampling. Data was collected using AI Anxiety scale (Wang and Wang, ٢٠٢٣), AI literacy scale (wang,Ru and Uan, ٢٠٢٣) and cognitive load questionnaire (Oktaviyanthi et al, ٢٠٢٤). The reliability of the questionnaires was evaluated using Cronbach's alpha coefficients, which were .٨٩, .٩١, and .٨٧, respectively—indicating high internal consistency. Additionally, content validity was assessed through the Content Validity Ratio (CVR), with all items scoring above ٠,٧٠, thereby confirming their acceptable level of validity. Data analysis was done with SPSS ٢٤ and SPLS ٣ software. The results showed that AI literacy has an effect on cognitive load, cognitive load has an effect on AI anxiety, and the effect of AI literacy on AI anxiety is significant (P<٠,٠١). Also, examining the indirect effect showed that cognitive load plays a mediating role in the relationship between AI literacy and AI anxiety. Overall, the results of the study indicate that perceived cognitive load can be an important psychological factor that shapes the path of AI literacy’s impact on AI-related anxiety. Understanding and managing this cognitive load plays a key role in reducing students’ anxiety and enhancing their technological learning experience. These results emphasize the importance of designing learning environments with controlled cognitive load and targeted training in enhancing students’ psychological experience when encountering smart technologies.

Keywords: Artificial Intelligence Literacy - Artificial Intelligence Anxiety-Cognitive Load.

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Introduction

Artificial intelligence (AI) in education has emerged as a rapidly evolving multidisciplinary field that leverages AI to enhance teaching, learning, instructional design, and assessment (Ouyang & Jiao, ٢٠٢١). AI applications are now widely adopted in universities and industries, ranging from data analytics platforms to writing assistants and intelligent tutoring systems. Students, particularly at the graduate level, are increasingly expected to use these technologies for research, communication, and problem-solving (Luckin et al, ٢٠١٦). Universities now encourage all students—not only those in computer science or AI-related disciplines—to develop the skills necessary for engaging with AI in their future careers (Southworth et al, ٢٠٢٣).

As AI becomes embedded in educational, professional, and everyday life, understanding how individuals interact with and emotionally respond to AI is essential (Long & Magerko, ٢٠٢٠).

Although AI is increasingly integrated into higher education, many graduate students report experiencing AI anxiety. It defined as stress or apprehension related to interacting with AI technologies (Shen et al, ٢٠٢٣).

AI anxiety encompasses fears that AI is uncontrollable or may negatively impact personal and social life (Kaya et al., ٢٠٢٢). Similar to earlier notions of computer anxiety (Nomura et al, ٢٠٠٨), AI anxiety refers to an overall affective response of anxiety or fear and feelings of agitation about out-of-control AI that inhibits an individual from interacting with AI (Johnson & Verdicchio, ٢٠١٧). Although AI anxiety is very similar to computer anxiety, there are some key differences. First, AI makes autonomous decisions; thus, it operates without human interference, leading to problems of artificial consciousness. Its decisions lack transparency, generating unpredictable risks. Second, when AI programs are making decisions, they use a large amount of data analysis to determine the strengths and weaknesses of action options, but human values and ethics are not considered, resulting in ethical violation issues(Wang et al,٢٠٢٢). Such anxiety can undermine motivation, lead to avoidance behaviors, and negatively affect academic performance and professional readiness (Shen et al., ٢٠٢٣).

Research consistently shows that AI literacy plays a key role in reducing AI anxiety (Zhang & Zhu, ٢٠٢٢). Higher AI literacy is associated with greater confidence and willingness to use AI tools, while lower literacy is linked to greater apprehension (Lee et al , ٢٠٢٤). AI literacy encompasses conceptual knowledge of AI, critical awareness of its societal impact, and practical skills to engage responsibly with AI systems without necessarily developing them (Wang, Cui, & Yuan, ٢٠٢٥).

Another critical factor linked to AI anxiety is cognitive load, which refers to the mental effort required to process information and complete tasks. Cognitive load theory (CLT) explains that learning is constrained by limited working memory, and excessive cognitive demands can increase stress and reduce performance(Sweller, ٢٠١١). Educational technology research shows that high cognitive load - often caused by new or complex systems- can result in frustration, disengagement, and technology-related anxiety (Su & Yang, ٢٠٢٣).

In the context of AI, students with lower AI literacy may experience higher cognitive load when interacting with AI systems, which in turn may exacerbate AI anxiety (Lee et al., ٢٠٢٤). Conversely, better AI literacy reduces cognitive load and supports more effective, less stressful engagement with AI technologies (Chen et al., ٢٠٢٤). Various researches have been conducted in this field, including: Zhang (٢٠٢٥) demonstrated that AI literacy improved teachers' AI self-efficacy and reduced job-related anxiety. Chen et al. (٢٠٢٤) found that AI learning self-efficacy mediated the relationship between AI literacy and classroom anxiety, while

Similarly, Cengiz & Peker (٢٠٢٥) showed that AI literacy and attitudes toward AI sequentially mediated the relationship between AI acceptance and AI anxiety among university students. Ayduğ and Altınpulluk (٢٠٢٥) also observed that AI anxiety was negatively associated with digital literacy among preservice teachers, emphasizing the importance of AI literacy in professional training. Moazami and Alimoradi (٢٠٢٥) also in a descriptive correlational study on students at the University of Tehran found that artificial intelligence tools have a positive and significant effect on students' cognitive load.

Omidi and Jame Bozorgy (٢٠٢٥) evaluated AI literacy and analyzed its conceptual structure among students of Allameh Tabatabaei University, focusing on three components of AI literacy, AI self-efficacy, and AI self-management using a descriptive-analytical method, and showed that the average scores of students in all three components were significantly higher than the theoretical average level. The students studied had a relatively favorable level of AI literacy.

Despite growing evidence linking AI literacy to reduced anxiety, few studies have examined whether cognitive load mediates this relationship, particularly among graduate students. Graduate students represent a critical population because they frequently engage with advanced AI-driven research tools and are preparing for careers in increasingly AI-augmented industries. This study seeks to address this gap by investigating whether perceived cognitive load serves as a mediating mechanism between AI literacy and AI anxiety among graduate students. Therefore, the research hypotheses are examined as:

١. AI literacy has a significant effect on AI anxiety.
٢. AI literacy has a significant effect on perceived cognitive load.
٣. Perceived cognitive load has a significant effect on AI anxiety.
٤. Perceived cognitive load plays a significant mediating role in the relationship between AI literacy and AI anxiety.

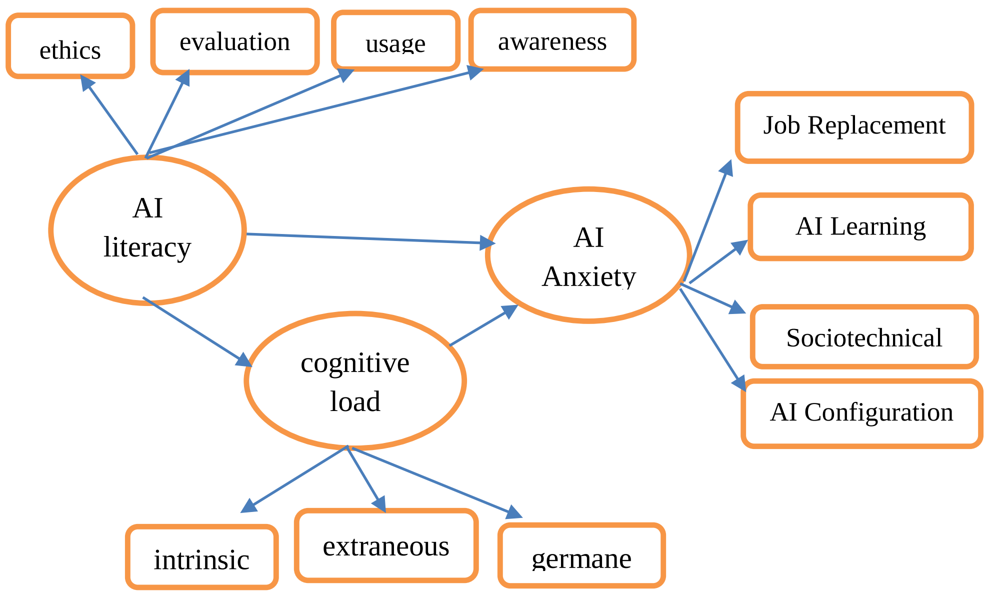

Figure ١: Research concept model

Methodology

A quantitative approach correlational research method was applied to achieve the research objectives. Partial least squares structural equation modeling (PLS-SEM) was employed to test both the direct and moderating effects among the study variables. The statistical population of the research was all postgraduate students (٣٢٠) (master's and doctoral) of the Islamic Azad University, Kazerun Branch. Based on the Krejci and Morgan table, ١٧٥ people were selected as the statistical sample of the research using simple random sampling.

Data were collected using a structured questionnaire comprising two sections. The first section collected demographic information, including age, gender, education level, and field of study.

The second section assessed the three main variables of interest: AI literacy, AI anxiety, and cognitive load. All scales employed a ٥-point Likert response format, ranging from ١ (strongly disagree) to ٥ (strongly agree).

AI anxiety was measured using the AI Anxiety Scale developed by Wang and Wang (٢٠٢٢), which includes ٢١ items across four dimensions: AI Learning Anxiety, Job Replacement Anxiety, Sociotechnical Blindness, and AI Configuration Anxiety. Reported reliability coefficients for these subscales are α = .٩٧ (Wang & Wang, ٢٠٢٢). AI literacy was measured using an adapted ١٢-item scale developed by Wang et al. (٢٠٢٣). This scale evaluates students' competence in four domains: AI awareness, practical usage, evaluation of AI technologies, and ethical considerations. Cognitive load was assessed using an adapted version of the cognitive load measurement framework proposed by Sweller et al. (٢٠١١). This instrument measures three components of cognitive load: intrinsic, extraneous, and germane cognitive load.

the reliability of the questionnaires was assessed using Cronbach's alpha coefficient, which exceeded ٠,٨٠, indicating high internal consistency. Additionally, the content validity of the questionnaires was evaluated using the

Content Validity Ratio (CVR), and all items scored above ۰,۷۰, confirming their validity.

A total of ۱۸۵ students with a mean age of ۳۲,۸ and a standard deviation of ٦,٤ participated in this study, ۸٤,۸٪ (۱٥۷ at the master's level) and ۲۸,۱٥٪ were studying at the doctoral level. ٥۸,۹۱ percent (۱۰۹ people) were women and ۱٤,۰۸ percent (۷٦ people) were men.

Research Findings

The partial least-squares structural equation modeling (PLS-SEM) approach was used to test the proposed research model. because It places minimal demands on sample size and residual distributions for estimating the model parameters .The normality of the data distribution was checked using the Kolmogorov-Smirnov test. As can be seen in Table ۱, all of the research variables were not normal and it was better to use the partial least squares method (PLS).

Table ۱- Kolmogorov-Smirnov for normality

	Kolmogorov-Smirnov -z	Sig
AI anxiety	۰.٤۹	۰.۲۳
AI literacy	۰,٥۱	۰.۲۱
cognitive load	۰,٥٥	۰.۲۲

The initial step in evaluating the measurement model in PLS was to assess indicator reliability through factor loadings. According to Heer and Ringel (۲۰۱۱), factor loadings should ideally exceed ۰,۷۰ to demonstrate adequate item reliability. However, items with loadings slightly below ۰,۷۰ can be retained if they do not negatively influence the overall model fit and are theoretically justified by their association with other indicators. Figure ۱ presents the initial reflective measurement model, displaying standardized coefficients for all indicators. As shown, all factor loadings exceeded the recommended threshold of ۰,۷۰, indicating satisfactory indicator reliability.

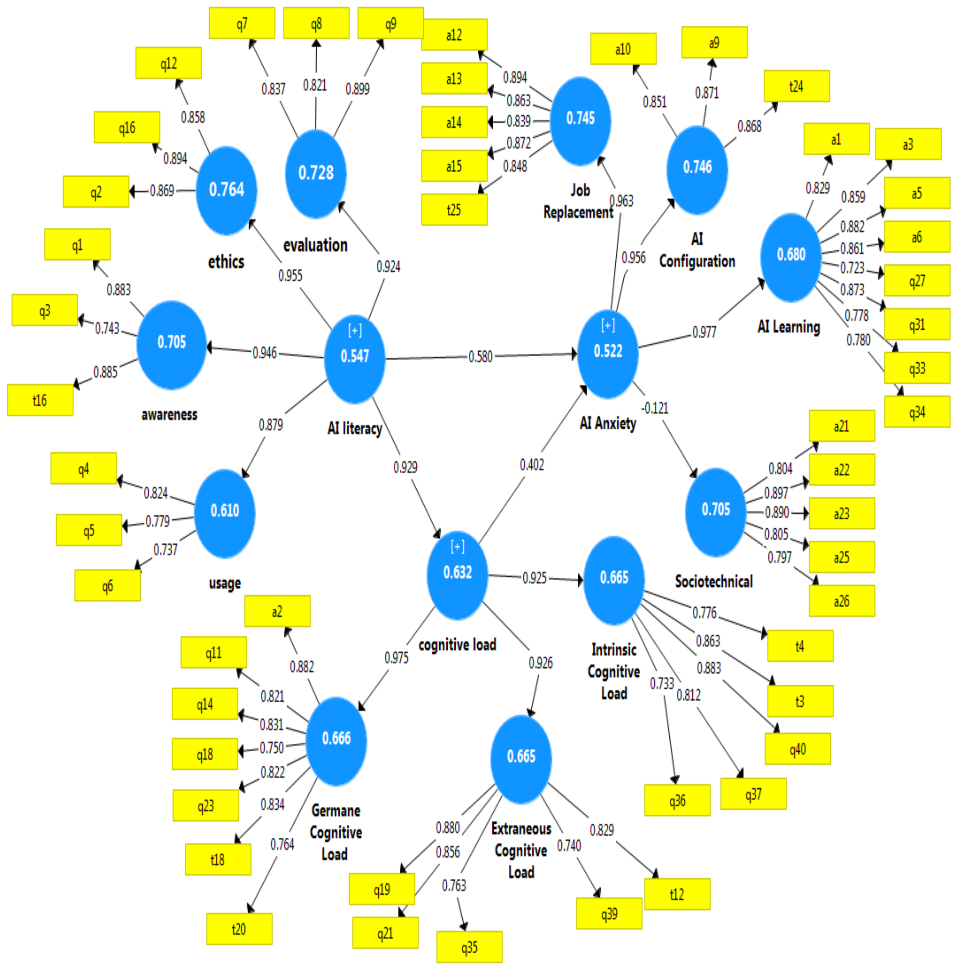

Figure ١ : standard coefficients

Table ١: Evaluation of Measurement Model

	AVE (≥٠,٥٠)	CA (≥٠,٧٠)	RHO_A (≥٠,٧٠)	CR (≥٠,٧٠)
AI anxiety	٠,٥٢	٠,٩٣	٠,٩٣	٠,٩٤
AI literacy	٠,٥٥	٠,٩١	٠,٩١	٠,٩٢
cognitive load	٠,٦٣	٠,٩٢	٠,٩١	٠,٩٥

As shown in Table ١, all reflective constructs demonstrated satisfactory reliability, as indicated by Composite Reliability (CR) values exceeding the recommended threshold of ٠,٧٠ for all variables. Convergent validity was also established through the Average Variance Extracted (AVE), which measures the amount of variance captured by a construct relative to the variance attributed to measurement error. All constructs reported AVE values above ٠,٥٠, indicating that each construct explains more than ٥٠٪ of the variance in its indicators (Hair et al., ٢٠١٤). These results confirm that the measurement model meets the standard criteria for internal consistency reliability and convergent validity.

Table ١: Evaluation of Measurement Model

	AVE (≥٠,٥٠)	**CA** (≥٠,٧٠)	RHO_**A** (≥٠,٧٠)	**CR** (≥٠,٧٠)
AI anxiety	٠,٥٢	٠,٩٣	٠,٩٣	٠,٩٤
AI literacy	٠,٥٥	٠,٩١	٠,٩١	٠,٩٢
cognitive load	٠,٦٣	٠,٩٢	٠,٩١	٠,٩٥

To further establish the discriminant validity of the reflective constructs, the Fornell–Larcker criterion was applied. According to this criterion, the square root of the Average Variance Extracted (AVE) for each construct should exceed its correlations with any other construct (Fornell & Larcker, ١٩٨١). As shown in Table ٢, the bolded diagonal values represent the square roots of the AVE for each construct, all of which are greater than their respective inter-construct correlations. These results confirm that each construct is empirically distinct from the others, thereby supporting discriminant validity

Table ٢. Discriminant Validity: The Fornell Larcker

	AI anxiety	AI literacy	cognitive load
AI anxiety	٠,٩٦	-	-
AI literacy	٠,٩٥	O.٩٣	-
cognitive load	٠,٩٤	٠,٩١	٠,٧٩

Another approach to assessing discriminant validity is through the examination of cross-loadings. According to Hair et al. (٢٠١٦), an item should exhibit a higher loading on its associated latent construct than on any other construct in the model. The results of this analysis confirmed adequate discriminant validity, as all items loaded more strongly on their respective constructs than on alternative constructs. Table ٣ presents the detailed cross-loading results supporting these findings.

Table ٣. Discriminant Validity: The HTMT

	AI anxiety	**AI literacy**	**cognitive load**
AI anxiety	-	-	-
AI literacy	٠,٨٩	-	-
cognitive load	٠,٨٦	٠,٨٨	-

To test the predetermined hypotheses, structural equation modeling (SEM) was conducted using the bootstrap method to assess indirect effects (Hair et al., ٢٠١٤). As shown in Table ٤, the results indicate that AI literacy is significantly related to cognitive load (β = ٠.٥٨, p < ٠,٠٥), supporting Hypothesis ١. Likewise, cognitive load was found to be significantly associated with AI anxiety (β = ٠.٤٢, p < ٠,٠٥), providing empirical support for Hypothesis ٢. Furthermore, AI literacy was also significantly related to AI anxiety (β = ٠.٩٢, p < ٠,٠٥), confirming Hypothesis ٣.

Table٤: Results of Path Coefficient: Direct Effects

Path	B	t	p.value
AI literacy - cognitive load	٠,٥٨	٧١,١٨	.٠٥
AI literacy - AI anxiety	٠،٩٢	١٠,١٩	.٠٥
cognitive load- AI anxiety	٠,٤٢	٧,٥٣	.٠٥

To assess the indirect effect of cognitive load, the bootstrap method was employed due to its robustness and accuracy in estimating mediation effects. The significance of the indirect relationship was evaluated using two criteria: (١) the significance level (p-value), and (٢) the ٩٥٪ confidence interval (CI) of the mediation effect. Specifically, if the lower and upper bounds of the ٩٥٪ CI are both either positive or negative, and the interval does not include zero,the mediation effect is considered statistically significant(Preacher & Hayes, ٢٠٠٨).

Table ٥: Results of Path Coefficient: Indirect Effects

Path	T	p.value	Bootstrap limits	
			Lower bound	Upper bound
AI literacy - cognitive load - AI anxiety	٦,٤٤	٠,٠٥	٠,٢٦	٠,٤٩

As shown in Table ٥, the bootstrap results indicate that cognitive load significantly mediates the relationship between AI literacy and AI anxiety. This finding confirms the hypothesized mediating role of cognitive load in linking AI literacy to AI-related anxiety

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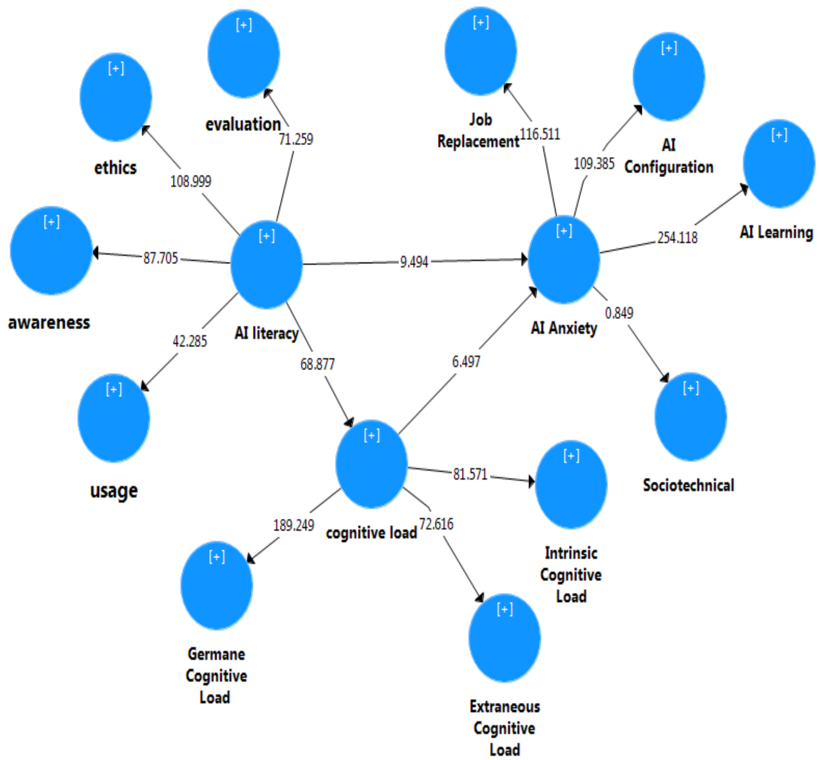

Figure۲: t-value

Discussion and conclusion

The present study investigated the relationship between AI literacy, cognitive load, and AI anxiety among university students, focusing specifically on the mediating role of cognitive load. The results indicate that cognitive load significantly mediates the association between AI literacy and AI anxiety. In particular, students with higher AI literacy experienced reduced cognitive load when engaging with AI-related concepts and tasks, which, in turn, was associated with lower levels of AI-related anxiety. Conversely, limited AI literacy was linked to heightened cognitive load and increased anxiety toward AI technologies

The negative relationship observed between AI literacy and AI anxiety is consistent with prior research demonstrating that technological literacy can alleviate fear and resistance to emerging technologies (Long & Magerko, ۲۰۲۰; Zhang & Dafoe, ۲۰۱۹). Increased literacy reduces uncertainty and enhances individuals' perceptions of control, thereby mitigating negative emotional responses (Ng, ۲۰۲۱). In the specific context of AI, literacy equips individuals with an understanding of the functionality, limitations, and implications of AI, reducing misconceptions and unfounded fears often rooted in a lack of exposure or knowledge (Yuen et al.,۲۰۲۱). The current findings align with these observations while extending existing knowledge by identifying cognitive processing as an underlying mechanism through which literacy influences emotional outcomes.

A key contribution of this study lies in the identification of cognitive load as a mediator. According to cognitive load theory, working memory has limited capacity, and excessive task complexity or unfamiliarity increases cognitive demands, which can result in negative affective states such as anxiety and frustration (Plass & Kalyuga, ٢٠١٩). While cognitive load has been extensively studied in educational technology contexts, including virtual reality learning (Makransky et al., ٢٠١٩) and intelligent tutoring systems (Kalyuga, ٢٠١١), its mediating role in AI-related emotional responses has received little attention.

The findings of this study contribute to filling this gap by illustrating that limited AI literacy may impose greater cognitive demands on learners, thereby amplifying anxiety. This aligns with emerging evidence from technology-enhanced learning, where cognitive load is recognized as a critical determinant of learner engagement, performance, and emotional well-being (Chen et al., ٢٠٢٢). The mediating effect observed here supports broader cognitive–affective frameworks that posit that higher mental effort, particularly when coupled with novelty and complexity, triggers avoidance behaviors and negative emotional reactions (Schunk et al., ٢٠٢٢).

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