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ORIGINAL CONTRIBUTION

AI Instructional Prescriptiveness and Adaptive Performance: Evaluating the Instructional Agency Paradox Through Cognitive Dependency and Perceived Autonomy

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Abstract— This article examines the extent to which AI Instructional Prescriptiveness (AIIP) impacts knowledge workers' Adaptive Performance (ADP) through Cognitive Dependency (CD) and Perceived Autonomy (PA). The moderating role of AI literacy was also examined. The focus is on the instructional agency paradox, where AI-driven instruction is counter to the human intelligence that the system is intended to augment. This study uses data from 202 knowledge workers using AI-prompted training tool(s) in their work processes. A purposive sample of workers in information technology firms in Pakistan was examined. A survey was conducted, and quantitative analyses were done using SPSS 29, and PLS-SEM was used through SmartPLS 4. The study identified that AI instructional prescriptiveness negatively predicts adaptive performance. Based on our theoretical arguments, the data could not confirm the mediation of perceived autonomy and cognitive dependency. In addition, contrary to the techno-optimists, AI Literacy did not moderate the impact, implying that upskilling is insufficient to counter design-constraining systems. As algorithmic management becomes a norm in people management, learning and development managers and systems architects need to think beyond prescriptive data and move to supportive frameworks. Organizations must understand that high-friction, prescriptive AI will likely create a digitally skilled but cognitively dependent employee. This research contributes to the expanding body of literature on artificial intelligence by addressing the autonomy and cognitive dependency pathways that explain performance-eroding processes.

Index Terms— Algorithmic management, AI literacy, Cognitive dependency, Adaptive performance, Instructional agency paradox, Human-AI collaboration

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Introduction

Artificial Intelligence (AI) has dramatically altered human-computer interaction within the workplace.AI systems have evolved beyond passive instruments for information retrieval but are becoming what ”Algorithmic Managers” are: flow managers, evaluators, and recommenders of action (Zhang et al., 2025). This change is evident in the development of the workforce, where algorithms are beginning to take on ”instructional agency” (Meijerink & Bondarouk, 2023). Although these augmented training systems provide instant operational efficiencies, they also create a potential cognitive and psychological burden for users. Some emerging theories on the ”duality” of algorithmic systems claim that while users are empowered in the short term, they are also simultaneously disempowered and even diminished in their ability to think critically (Jiang et al.,

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2025). This ”Instructional Agency Paradox” describes how, because AI instructors are also highly efficient and exert prescriptive control and corrective feedback, users can develop learned helplessness (Ghaedipour, 2022).

There has been considerable focus in past studies on explaining adoption barriers from a techno-optimist perspective as opposed to explaining the implications of the embedded technology (Wissuchek & Zschech, 2024). It has been suggested “in common sense” that upskilling employees will reduce the threats (W. Wang et al., 2022). This is the case even though the assumption that the educated user is an emancipated user is quite untested, especially in the case of restrictive AI systems. To bridge the existing gaps in the literature and be informed by Self-Determination Theory (SDT), we examine the extent to which AI instructional prescriptiveness influences Adaptive performance of knowledge workers. We hypothesize that employees working in an environment with highly prescriptive systems will experience a change in the locus of causality that will manifest as a decrease in Perceived autonomy and an increase in Cognitive dependency (Hopper, 2025). We also look at AI literacy as a moderator to determine if the presence of a prescribed system along with technical knowledge gives individuals the sense of autonomy that is often believed to be missing in such systems.

This study empirically substantiates the paradox of Augmentation by bringing prescriptive design into the discussion of cognitive offloading. It criticizes the Literacy-as-Panacea narrative by showing that system design often prevails over user ability. The necessity of conducting this research becomes even more acute owing to the fast institutionalization of AI-enabled systems in the knowledge-based industries where decision-making independence was a crucial component of expertise. With the implementation of prescriptive AI in various organizational processes, the nature of expertise will be changing from being reflective and judgment-based to being directive and system-supported (Ahmad, 2025; Meijerink & Bondarouk, 2023). Such a tendency poses serious concerns not only regarding the possible impact of using AI on employee performance but also concerning its sustainability and long-term results. If workers are dependent on AI guidance, there is an obvious risk that their creativity, problem-solving abilities, and critical thinking skills may be impaired to a significant extent (Ghaedipour, 2022; Jiang et al., 2025). However, there is a lack of empirical studies dedicated to understanding how particular characteristics of AI can influence the described issues.

In addition, this research addresses a widening gap between the managerial perceptions and actual experiences of employees working in AI-driven settings. Although organizations are keen on investing in AI literacy programs based on the assumption that technical know-how will inevitably lead to empowerment, such an approach does not account for limitations that emerge due to organizational structures created within the system (B. Wang et al., 2022; Wissuchek & Zschech, 2024). Under a rigid organizational structure, employees, despite being competent in using the technology, can still see their empowerment stifled by the very nature of the system, since it not only defines the required course of action but also determines its implementation (Hopper, 2025). Hence, by investigating the role played by AI literacy in the proposed research design, it becomes possible to challenge the dominant viewpoint of knowledge as a panacea for overcoming algorithmic control. From this perspective, the research sheds light on the relationship between employee capabilities and the organizational structure designed through technological innovations (B. Wang et al., 2022; Zhang et al., 2025).

Theory and Hypothesis Development

Self-Determination Theory and the autonomy paradox

Self-Determination Theory outlines the relationship between external factors and motivation and performance. The paradox of autonomy theory defines autonomy as the individual’s need to feel as though they are the origin of the activity. With regard to control in AI, this, in many instances, is undermined by the “illusion of control” (Ghaedipour, 2022). With the transformation of AI systems from tools to support decision-making to “Algorithmic Bosses” through prescriptive analytics, they remove user decision-making (Wissuchek & Zschech, 2024).

AI instructional prescriptiveness and adaptive performance

To better comprehend the connection between AI instruction prescriptiveness and adaptive performance, there could be a need to examine how research from adjacent areas like work design, cognitive psychology, and information systems is applicable. The fact that AI instruction prescriptiveness involves rule-driven instructions, automation, and restricted decision paths means that it is likely to result in a uniform way of doing things and reduce the variation in performance. The problem with this, however, is that it would not give the workers an opportunity to utilize their cognitive resources to make sense of the task, explore various alternatives, and learn new things. Adaptive performance requires an individual to adapt to change, apply what they have learned in a different setting, and come up with creative solutions to problems. Using the Job Demands-Resources (JD-R) theory, overly prescriptive systems might act as hindrance demands that limit the worker’s control and discretion (Bakker & Demerouti, 2007). Similarly, research related to cognitive load theory posits that although structured guidance can help lower extraneous load initially, over-reliance on external instructions can negatively affect germane cognitive load processes, which are integral to schema development and transfer. Taking into consideration sociotechnical systems theory, the presence of inflexible technologies can cause misfitting between human adaptability and technological constraints, thus compromising the overall resiliency of a system (Trist & Bamforth, 1951). Research in automation bias also indicates that people working in directive environments can become overconfident in automated systems and make minimal use of their judgment skills, especially in complicated situations (Parasuraman & Riley, 1997). Such behavior is caused by a limited chance for learning, as proposed by experiential learning theory, which states that adaptation comes about through repeated cycles of action and reflection (Kolb, 1984).

Moreover, studies in the domain of dynamic capabilities stress that the ability of individuals to adapt to environmental changes is essential, but this capability is hampered when employees are limited by rigid and prescriptive systems (Judijanto & Nurhayati, 2026; Teece, 2018). Lastly, research on human-AI collaboration indicates that when individuals are seen as passive users of algorithmic directions instead of active decision-makers, their feeling of accountability decreases, further affecting their ability to make adaptive adjustments to situations (Shneiderman, 2020). Altogether, these theories support the notion that while AI instructional prescriptiveness may provide benefits for the organization in terms of increased efficiency and consistency, it limits the ability of individuals to engage in adaptive performance due to low levels of cognitive processing, lack of autonomy, and reduced exploration. Adaptive performance is defined by the extent to which a person adjusts their behavior in response to the demands of a novel situation (Charbonnier-Voirin & Roussel, 2012). We argue that this performance is predicted negatively by high AI instructional prescriptiveness, a situation where systems control how and in what order the learners should proceed. AI controlling work processes renders people as "data laborers" and leads to a decline in psychological engagement (Gong, 2025). Thus, we state the following hypothesis:

H1: AI instructional prescriptiveness and adaptive performance are negatively related.

Mediating role of perceived autonomy

Perceived autonomy captures the degree to which an individual believes they can act in accordance with their own values and interests rather than being directed by external forces. In this case, when the locus of control shifts from the person to the machine, the need for autonomy is considered undermined (SDT). Lippert (2025) posits that this creates a "hollowing-out" of role identity. We suggest that the impact of prescriptiveness on negative performance is channeled through diminished agency.

Perceived autonomy acts as a critical mediator in the connection between AI instructional prescriptiveness and adaptive performance, providing an explanation of how the psychological process takes place. AI instructional prescriptiveness, being what it is, provides guidance, sets guidelines, and feedback that take away user freedom in performing assigned tasks. This may help increase productivity; however, it reduces a person's feeling of freedom in acting out his/her intentions. According to Self-Determination Theory, autonomy is one of the basic psychological needs that foster intrinsic motivation and cognitive flexibility (Deci & Ryan, 2000). With such a need being restricted by extremely prescriptive AI applications, workers will be more susceptible to experiencing controlled motivation as opposed to autonomous motivation, hence reducing their likelihood and capability to adapt to new and unforeseen circumstances. Adaptive behavior involves people trying out new things, breaking routines, and reacting creatively to change, a process that is greatly undermined by decreased autonomy. Empirically, the relationship between lower autonomy levels at work and poor learning orientation and adaptability has been documented in the context of work design (Akram et al., 2024; Begum et al., 2025). Besides, empirical studies on algorithmic control mechanisms reveal that, as people see their activities as guided by smart machines, they tend to reduce engagement and adopt compliance strategies (B. Wang et al., 2022). Such a phenomenon not only reduces intrinsic motivation but also hampers the development of adaptive skills. Thus, perceived autonomy becomes an important mediating variable through which AI instructional prescriptiveness affects adaptive performance, namely by limiting the cognitive flexibility, motivation, and initiative required for the latter.

H2. Perceived autonomy is the mediator in the relation between AI instructional prescriptiveness and adaptive performance.

Mediating role of cognitive dependency

Cognitive dependency serves as a mediating mechanism that elucidates the "cognitive costs" of AI adoption, commonly termed the "Paradox of Augmentation" (Macnamara et al., 2024). This is through "cognitive offloading," in which users see the AI as an external memory storage and not as a collaborator (Hopper, 2025). Relying on AI too much contributes to a "skill decay" where users are less likely to monitor the AI. We contend that prescriptiveness creates dependency, which subsequently diminishes the ability to tackle unscripted problems. The implication becomes especially critical in regard to adaptive performance, which is dependent on flexible thinking, independent decision-making, and effective responses to new and complicated environments. Cognitive dependency limits these abilities by limiting the range of solutions available to the user and creating habits of always relying on the same answer. Moreover, the theory of cognitive offloading indicates that people who depend on technology to perform their thinking processes will find themselves losing their cognitive skills over time. Within an organizational setting, this is further compounded by the presence of algorithmic management systems, wherein these algorithms do not just suggest, but also implicitly set the parameters within which decisions must be made, hence entrenching dependency patterns. Additionally, according to learning theories, in-depth learning and knowledge transfer depend on engagement and reflection; however, cognitively dependent learners have a tendency to avoid engaging in reflective thought processes, thus hindering their capacity for adapting to novel situations (Chi & Wylie, 2014; Mehmood, 2025). Consequently, while instructional prescriptiveness through AI does enhance efficiency in performing familiar tasks, it simultaneously curtails the learner's ability to think critically and learn from experience, hence hindering their adaptive performance in the workplace.

H3. Cognitive dependency is the mediator in the relation of AI instructional prescriptiveness and adaptive performance.

Moderating role of AI Literacy

The ability to understand and critique the outputs of AI systems is called AI Literacy. It aids in the mitigation of automation bias (Cetindamar et al., 2022). There is a belief that a user competent in AI literacy is able to “negotiate” with an algorithm. Contrary to this belief, however, research shows that platform trust is often more dominant than platform literacy (Reisdorf & Blank, 2021). The assumption we are testing is whether high literacy, in this case AI literacy, is likely to buffer the negative effects of prescriptiveness.

The moderating effect of AI literacy on the influence of AI instructional prescriptiveness on adaptive performance may be seen as a form of cognitive buffering process that affects how people interpret AI guidance. When algorithms become overly prescriptive, they tend to decrease personal autonomy and induce passivity. In turn, people who are more literate regarding AI can think more critically about algorithmic advice and select the most useful elements from it instead of blindly accepting it. Apart from technical knowledge about how particular algorithms work, AI literacy implies a grasp of system limits, potential biases, and optimal usage conditions. As noted recently, AI-competent people have greater chances of becoming actively involved in their communication with intelligent agents through cognitive reflection rather than being cognitively passive (Dellermann et al., 2019; Long & Magerko, 2020). This approach is less prone to leading to cognitive dependence and automation bias, which makes it possible to preserve adaptability.

Additionally, recent investigations into the topic of human-AI interaction reveal that the role of the employee’s skills and knowledge affects the extent to which AI systems are beneficial or limiting to humans. Higher levels of employees’ literacy in the area help to overcome or modify suggestions made by prescriptive algorithms for new and unusual cases, thus eliminating the constraining effects of prescriptive design on their ability to adapt and perform (Raisch & Krakowski, 2021). Those who possess lower literacy, however, can view the prescriptive instructions as mandatory and authoritative, which leads to high levels of compliance but low adaptability in response to changes. Empirical research also shows that possessing certain digital and AI-specific abilities increases employees’ feeling of control, allowing for better adaptation and use of technology in decision-making processes (Glikson & Woolley, 2020; H. Wang et al., 2023). AI literacy thus acts as a moderator of the link between AI instructional prescriptiveness and employees’ adaptive performance. Its positive impact is manifested in the decreased adverse effect of the former on the latter.

H4. AI literacy moderates the relationship between AI instructional prescriptiveness and adaptive performance, such that the negative effect is attenuated among employees with higher AI Literacy.

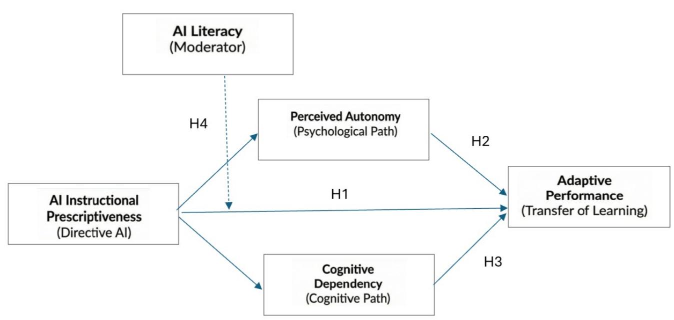

Fig. 1 *Conceptual model*

Methodology

Sampling and data collection

Data were collected from knowledge workers to evaluate the proposed research model. The knowledge workers included those using AI-enabled training or decision-support tools (e.g., learning management systems, generative AI assistants) as part of their workflows. Participants were identified via purposive professional networking (LinkedIn) and internal organizational email list(s). The final sample consisted of 202 professionals based on the completeness of their responses. For the sample, we shortlisted the firms listed with the Pakistan Software Export Board (PSEB). The employees belong to these firms and work as full-time employees exposed to AI prescriptive training. The respondents were mainly male, with 117 respondents representing 57.92%, and female 85 representing 42.08%. This means that there was a higher proportion of male participants in the study, using the sample from IT firms. In terms of age, the largest group was 26–33 years, with 63 respondents, or 31.19%, followed by 18–25 years, with 49 respondents, or 24.26%. The majority of respondents (71, 35.15%) had 1- 5 years of work experience, followed by those with 6- 10 years of work experience (57, 28.22%). In general, the sample was dominated by young and early-stage male respondents with moderate levels of professional experience.

Measures

The constructs were measured based on relations to various studies. All constructs were assessed using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

AI instructional prescriptiveness

For this construct, the 4-item "Directing" subscale of the COMAMA Scale by Röttgen et al. (2025) was used. This assesses how the system evaluates learning objectives uniquely (e.g., "The AI system tells me what I should do to complete the learning tasks"). The internal consistency was very good (alpha = 0.828).

Perceived autonomy

This was measured using the 6-item subscales of the Work Design Questionnaire (WDQ) by Morgeson and Humphrey (2006) (e.g., "The training gives me the freedom to decide what methods I use"). The scale had reliability in the acceptable range (alpha = 0.64).

Cognitive dependency

This was adapted from the 5-item "Monitoring" subscale of the AICP-R scale (Merritt et al., 2019). An example item is "It is not usually necessary to pay much attention to the AI when it is running." Reliability was also within an acceptable range (alpha = 0.638).

Adaptive performance

Assessed using 7 items from the Adaptive Performance Scale (Charbonnier-Voirin & Roussel, 2012) on creativity and reactivity (e.g., "I develop new tools and methods to resolve new problems". Reliability was excellent (alpha =0.897).

AI Literacy (Moderator): B. Wang et al. (2022) 12-item scale on Awareness, Usage, Evaluation, and Ethics. Reliability was good (alpha = 0.795).

Analyses and Results

Table I

Descriptive statistics and correlations

No.	Variable	Mean	SD	1	2	3	4	5
1	AIIP	3.31	0.71	1				
2	CD	3.15	0.87	0.500*	1			
3	AIL	3.76	0.56	0.542**	0.533**	1		
4	ADP	3.50	0.79	-0.083*	-0.011**	-0.030**	1	
5	PA	3.57	0.72	0.458**	0.303	0.357 **	-0.122 *	1

Note: **Correlation is significant at the 0.01 level (2-tailed); * Correlation is significant at the 0.05 level (2-tailed).

Note: AIIP = AI Instructional Prescriptiveness, CD = Cognitive Dependency, AIL = AI Literacy, ADP = Adaptive Performance, PA = Perceived Autonomy.

Descriptive statistics and correlations

Descriptive statistics and correlations between the variables of the study are summarized in Table I. The mean scores show that AI literacy had the highest mean value, M = 3.76, SD = 0.56, followed by perceived autonomy, M = 3.57, SD = 0.72, and adaptive performance, M = 3.50, SD = 0.79. The mean score was moderate for AI instructional prescriptiveness, M = 3.31, SD = 0.71, and the lowest mean score was for Cognitive dependency, M = 3.15, SD = 0.87. There were positive correlations between AI instructional prescriptiveness, on one hand and cognitive dependency (r = 0.500), AI literacy (r = 0.542), and perceived autonomy (r = 0.458). There was also a positive correlation between cognitive dependency and AI literacy (r = 0.533) and perceived autonomy (r = 0.303). Perceived autonomy was found to be positively related to AI literacy r = 0.357. Weak negative relationships were observed between Adaptive performance and AI instructional prescriptiveness, cognitive dependency, AI literacy, and perceived autonomy. In summary, AI instructional prescriptiveness had the highest correlation, and cognitive dependency had the lowest correlation with all other factors.

Table II
Measurement model tests

Variable	VIF	CR	AVE	Cronbach's Alpha
AI Instructional Prescriptiveness	1.792	0.832	0.660	0.828
Cognitive Dependency	1.439	0.637	0.477	0.638
AI Literacy	1.101	0.655	0.495	0.795
Adaptive Performance	1.21	0.915	0.658	0.897
Perceived Autonomy	1.511	0.602	0.522	0.64

Note. VIF = Variance Inflation Factor; CR = Composite Reliability; AVE = Average Variance Extracted. Source: Authors' own work

The measurement model outcomes indicated that none of the VIF values were greater than 1.792 or less than 1.101, suggesting no serious multicollinearity problems among the constructs. The reliability and validity of AI instructional prescriptiveness were good, with CR = 0.832, AVE = 0.660, and Cronbach's Alpha = 0.828. Adaptive Performance also demonstrated good measurement quality, as reflected in CR = 0.915, AVE = 0.658, and Cronbach's Alpha = 0.897. The results for cognitive dependency were not as strong as the others, with the CR being equal to 0.637, AVE being 0.477, and Cronbach's Alpha being 0.638, which meant that it had only marginal reliability and slightly weak convergent validity. The other constructs, Perceived autonomy, performed moderately well with a CR value of 0.602 and a Cronbach's Alpha of 0.640, with an AVE of 0.522. The measurement of AI literacy depicted acceptable internal consistency of the scale with an alpha of 0.795 and a CR of 0.655. However, the AVE was 0.495, which is close to the 0.50 threshold for good convergent validity. We predict that the multidimensional nature of AI literacy should be part of future studies.

Table III
Discriminant validity using HTMT

Variable	1	2	3	4	5
AI Instructional Prescriptiveness	1				
Cognitive Dependency	0.099	1			
AI Literacy	0.128	0.716	1		
Adaptive Performance	0.153	0.892	0.713	1	
Perceived Autonomy	0.169	0.788	0.818	0.744	1

HTMT < 0.90 indicates good discriminant validity

The HTMT values indicate good discriminant validity between all the study variables. The results showed that all the HTMT values were lower than the recommended value of 0.90, which means that the constructs were different from each other. The highest HTMT value was obtained between cognitive dependency and adaptive performance, HTMT = 0.892, which is near the threshold but considered acceptable. Other relatively high values ranged from AI literacy—perceived autonomy, HTMT = 0.818, cognitive dependency—perceived autonomy, HTMT = 0.788, and adaptive performance—perceived autonomy, HTMT = 0.744. The lowest HTMT value was between AI instructional prescriptiveness and cognitive dependency (HTMT = 0.099). In general, the results indicate fairly good measurement model discriminant validity.

Table IV
Hypothesis testing (Path analysis)

Paths	Coefficient β	SE	*t*-value	*p*-value		
AIIP -> ADP	-0.195	0.099	1.963	0.050		
AIIP -> PA	0.571	0.059	9.663	0.000		
PA -> ADP	0.053	0.103	0.515	0.607		
AIIP -> CD	0.528	0.062	8.494	0.000		
CD -> ADP	0.135	0.111	1.214	0.225		
Bootstrap results					LL	UL
					95% CI	95% CI
Indirect effect of AIIP -> PA -> ADP	0.168	0.062	0.497	0.619	-0.079	0.156
Indirect effect ofAIIP -> CD -> ADP	-0.029	0.059	1.156	0.248	-0.043	0.200

Note: AIIP = AI Instructional Prescriptiveness, CD = Cognitive Dependency, AIL = AI Literacy, ADP = Adaptive Performance, PA = Perceived Autonomy; I= Confidence Interval, UL=Upper Limit, LL=Lower Limit, SE=Standard Error. Direct effects are reported from the moderation model.
Source: Author's own work

The path analysis results show that AI instructional prescriptiveness had a significant positive effect on perceived autonomy, *β* = 0.571, *t* = 9.663, *p* = 0.000. A higher level of AI instructional prescriptiveness was correlated with higher perceived autonomy. AI instructional prescriptiveness was also found to significantly and positively affect cognitive dependency (*β* = 0.528, *t* = 8.494, *p* = 0.000), indicating that the more AI was used to instruct, the higher the cognitive dependency. No significant effect was found for perceived autonomy on adaptive performance, *β* = 0.053, *t* = 0.515, *p* = 0.607. Similarly, cognitive dependency was not significant for adaptive performance, *β* = 0.135, *t* = 1.214, *p* = 0.225. Likewise, the direct effect of AIIP on ADP was significant at the 0.05 level, which is the threshold of acceptance and cannot be considered a strong relationship. This outcome shows that the traditional approach of keeping *p*= 0.05 and thus staying on the borderline of acceptance. Further, the mediation results demonstrate that perceived autonomy does not mediate the relationship between AI instructional prescriptiveness and adaptive performance, as the 95% CI includes the null value. The indirect effect via cognitive dependency was also negligible, as the p-value was greater than 0.05 and the confidence interval contained 0. Overall, the results confirmed the direct effects of AI instructional prescriptiveness on perceived autonomy and cognitive dependency, but not on adaptive performance and mediation effects.

Table V
Moderation analyses

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	*T* statistics (|O/STDEV|)	*p* values
AIIL -> ADP	-0.162	-0.021	0.251	0.644	0.520
AIIL x AIIP -> ADP	-0.052	0.016	0.079	0.658	0.511
AIIP -> ADP	-0.195	-0.198	0.099	1.963	0.050
AIIP -> CD	0.528	0.535	0.062	8.494	0.000
AIIP -> PA	0.571	0.576	0.059	9.663	0.000
CD -> ADP	0.135	0.135	0.111	1.214	0.225
PA -> ADP	0.053	0.060	0.103	0.515	0.607

In this study, the moderation effect is not present, as the interaction term AIIL × AIIP -> ADP is not statistically significant, with *β* = -0.052, *t* = 0.658, and *p* = 0.511. The *p*-value is higher than 0.05, and the *t*-value is less than 1.96; therefore, AIIL does not have a significant moderating effect on the relationship between AIIP and ADP. This does not significantly influence the effect of AIIP on ADP. .

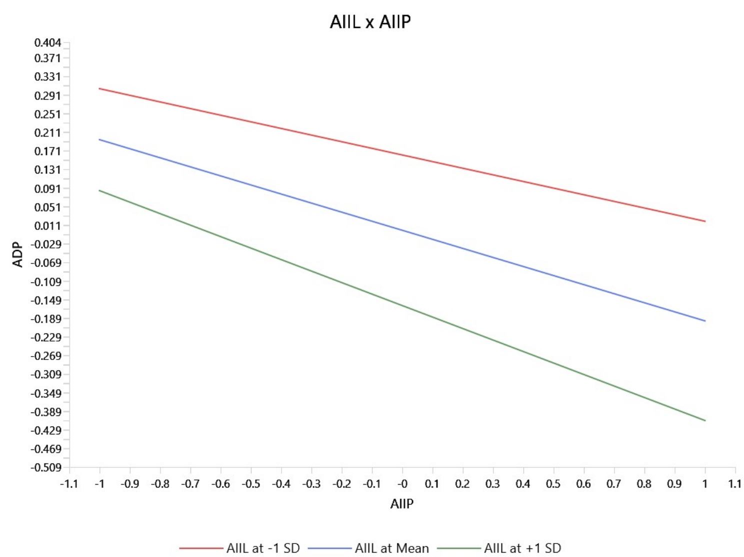

Fig. 2 *Moderating effect*

is rejected. This graph demonstrates that there is a negative correlation between AIIP and ADP at all three levels of AIIL. The higher the AIIP, the lower the ADP. The red line is low AIIL, the blue line is average AIIL, and the green line is high AIIL. The graph visually shows that there is a negative association between AIIL and ADP, and a positive association between AIIL and ATP. It also indicates that the green line is a little bit steeper, suggesting that the reduction of ADP is a little bit greater if AIIL is high. However, the interaction effect AIIL × AIIP -> ADP does not support this moderation statistically since it has a *p*-value of 0.511. The result, then, is not strong enough to be considered a moderate association, but there is a weak visual pattern.

Discussion and Conclusion

This study explored the understanding of using AI as an instructional prescriptiveness for adaptive performance. Contrary to the theoretical underpinning, Hypothesis 1, containing the direct effects, couldn't be fully substantiated. The very threshold significant value pertains to weak significance, which has been contradictory to what we had expected. Hypothesis 2 was about mediation of perceived autonomy between AIIP and ADP, which also couldn't be realized, and another direction, namely a positive effect of AIIP on PA, has been witnessed. This can be explained by Self-Determination Theory (Deci & Ryan, 2000), which suggests that autonomy is concerned with volition and self-endorsement and not only control by external sources. We argued that PA would be decreased in the presence of AI prescriptiveness; however, according to Self-Determination Theory (Deci & Ryan, 2000), autonomy is concerned with volition and self-endorsement and not only with control from external sources. Thus, we can infer that AIIP may enhance perceived autonomy as depicted by our results, as AIIP may induce facilitation in choosing. Thus, we can infer that AIIP may enhance perceived autonomy as depicted by our results, as AIIP may induce facilitation in choosing rather than an assumed negative association.

Although AIIP predicted cognitive dependency, the mediation of cognitive dependency couldn't be realized between AAIP and ADP. These findings pointed out new pathways which can serve as a mechanism for translating AIIP towards performance and particularly adaptive performance. Since AI-related studies are finding the same novel phenomenon as in our study, which includes AI in processes, it is worth exploring, predicting, and even getting results other than predicted in this emerging field. Consistent with this emergent nature of the field, Jiang et al. (2025) and Zhang et al. (2025) also endorsed the complexity of algorithmic control of AI and employee autonomy and empowerment, which needs to be explored. Most notably, the study explains how AI-enabled techniques can be used in the prediction of human behavioral outcomes, most probably performance. Since the study couldn't establish a direct, strong effect, it has uncovered the dynamics of this phenomenon in terms of psychological bridging between the direct effect and the realized one, 'not to do' in an organizational context.

Theoretical implications

By integrating Self-Determination Theory with the Paradox of Augmentation, this research provides novel theoretical insights into the cognitive and behavioral implications of AI use. First, we broaden the "Autonomy Paradox" to knowledge work. Most literature has focused on this in the gig economy (Kešāne & Spuriņa, 2025). We use this in the corporate training setting, being the first to support Lippert (2025) claim that algorithmic management "hollows out" professional expertise. Second, we address the "Paradox of Augmentation" empirically. For some time, theoretical models have stated the danger of short-term efficiency gains and the loss of long-term skills (Wissuchek & Zschech, 2024). Cognitive dependency has been shown to support Hopper (2025) that generative ability has shifted from offloading thinking to delegative thinking. We also dispute the 'Literacy-as-Panacea' narrative. Unlike the overly optimistic perspective we observe in HRD literature (e.g., Azhar et al., 2025), our non-significant moderation effect suggests a boundary condition for the literacy theory. It posits a sociometrical view (Orlikowski, 2007) frame that if a system is designed to be a "boss," user training will not be able to convert it to a "tool."

Building on these contributions, this study also advances the understanding of how algorithmic systems reshape the micro-foundations of learning and expertise development in organizational contexts. Prior research in Human Resource Development has largely assumed that continuous exposure to digital tools naturally leads to skill enhancement and capability growth (Azhar et al., 2025). However, our findings suggest that when AI systems are designed with high instructional prescriptiveness, they may instead shift learning from an exploratory, reflective process to a compliance-driven process, where employees focus on following system outputs rather than developing independent judgment. This aligns with sociometrical perspectives, which argue that technology and human action are co-constituted, meaning that system design actively shapes what users can and cannot become within a work context (Orlikowski, 2007). In this sense, AI does not merely support work it configures the boundaries of cognition and learning itself.

Practical implications

In this regard, we offer a set of practical managerial implications. First, for developers, the implication is that frictionless experiences are not always learning-friendly. Designers need to shift from prescriptive analytics that "tell" the user the answer to responsive analytics that offer the user a choice. Systems need "cognitive forcing functions" (Macnamara et al., 2024) to be designed to compel users to think and integrate knowledge. Second, for human resources and leadership managers, the focus has to be on procurement strategies. While 'buying' 'smart' AI tools may create a level of efficiency in the short run, organizations may risk decreasing long-term training initiatives. Training should focus on "how to ignore the tool" rather than "how to use the tool" (Kulal, 2025).

Limitations and future research

Drawing from the above contributions, there are various limitations that need to be highlighted for a proper understanding of the implications of the results. Firstly, it must be noted that self-reporting measures for AI instructional prescriptiveness, cognitive dependency, and adaptive performance were used in this research; thus, they may lead to common method bias and the overestimation of their associations. While there are ways to avoid this problem by employing procedures and statistics, it is always advisable to incorporate multi-method or objectively based performance indicators in order to enhance causal inference. Secondly, the cross-sectional design employed in the present work does not allow for an analysis of the complex and possibly cumulative process of AI exposure.

Moreover, the third limitation is that the contextual setting of the study (knowledge workers in structured organizations) may restrict the generalization of the results to other types of work environments, including the creative industries, gig work, or very unstructured jobs in which the interactions with AI could be rather different. Fourth, differences in organizational culture, managerial styles, and complexity of the tasks at hand were not taken into account explicitly, although they can substantially affect employees' perceptions of AI prescriptiveness. Finally, although the concept of AI literacy was explored as a moderator, it was treated generally and did not differentiate various dimensions (technical literacy, critical thinking concerning AI, ethical literacy). Since measuring AI literacy was a little below the threshold of AVE, we predict that the multidimensional nature of AI literacy should be more variable to be used by future studies. This weak construct validity of the AI literacy construct is reflected in the results of the study. Similarly, the unexpected effect of AIIP on PA realized by the study can be a theoretical limitation because it tends to challenge the existing notion of autonomy-based prescriptiveness of AI for performance. This limitation might be addressed in future research by elaborating on the conceptual definition of AI literacy. All in all, it can be concluded that although the current study provides useful findings both theoretically and empirically, additional research needs to be conducted to investigate the boundaries of those findings in terms of time and circumstances.

Conflict of Interest

The authors declare that they have no conflict of interest regarding the publication of this manuscript.

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Author Contributions

All authors made substantial contributions to the conception and design of the study, data collection, data analysis and interpretation, and manuscript preparation. All authors critically reviewed the manuscript, approved the final version, and agree to be accountable for all aspects of the work.

Informed Consent

Informed consent was obtained from all participants involved in this study prior to data collection.

Use of generative AI

The authors confirm that Generative Artificial Intelligence (AI) tools were used solely for minor language editing and grammatical refinement. These tools did not contribute to the study design, data collection, data analysis, interpretation of results, or the intellectual content and conclusions of the manuscript. The authors take full responsibility for the accuracy, originality, and integrity of the work.

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