



How AI-Supported Leadership Foster Employees AI-Driven Innovative Work Behavior: Unpacking the Mediated Moderation Mechanism

Qodirov Jovid^{1*}, Zhang Li^{1*}, Waqas Khuram² and Piatkova Ekaterina¹

¹ School of Management, Harbin Institute of Technology, Harbin, China

²Department of Management & HR, Institute of Business Management, Pakistan

*zhanglihit@hit.edu.cn

Abstract. This study proposes that artificial intelligence- supported leadership enhanced employees' AI-driven innovative work behavior through structures AI-training programs with organizational innovative climate serving as a reinforcing factor. While AI-driven leadership is increasingly adopted, its interaction with training initiatives and organizational climate serving as a moderator remains underexplored. Grounded in the Conservation of Resource (COR) theory, this research examines how AI-supported leadership directly and indirectly via AI-training programs foster employees innovative work behavior, while organizational innovative climate positively moderates these relationships. Survey data from 321 top and middle level managers in Russian high-tech organizations were collected and analyzed through SPSS-26. The results confirm all the hypotheses positively: (1) AI-supported leadership directly increases employees AI-driven IWB, (2) AI-training programs mediate this relationship and (3) organizational innovative climate strengthens the effects of both AI-supported leadership and training programs on AI-driven IWB. The results underscore the integrative and synergetic value of aligning technological leadership with human capital development with conducive organizational environment. From practical standpoint, the study highlights the imperative for organizational leaders to harmonize AI capabilities with continuous employee development and innovation-supported climates to sustainable drive innovation performance.

Keywords: Artificial intelligence, supported leadership, Training Program, Innovative Work behavior, Organizational Innovative Climate

1 INTRODUCTION

The rapid proliferation of artificial intelligence (AI) technologies is transforming organizational ecosystem by reinforcing leadership practices ^[1], redefining employees' roles and accelerating innovation trajectories ^[2, 3]. As organization navigate complex, technology-intensive environment, the integration of AI into strategic and operational domain has become not only a necessity but a catalyst for sustainable competitive advantage ^[4]. In this evolving landscape, AI-supported leadership-which refer to leadership practices that are augmented by AI tools and capabilities. This synergy

optimizes leaders' efficiency, insight quality and responsiveness while conserving cognitive resources. One of the most compelling implicating of AI-supported leadership lies in its capacity to stimulate the AI-driven Innovative work behavior — the proactive generation, promotion and implementation of novel ideas facilitated through AI-systems [4]. While prior research has addressed leadership's influence on employee's innovation broadly, limited scholarly attention has been directed towards understanding how AI-supported leadership style foster innovative behavior specifically in AI-enabled context [1]. This lack of clarity becomes salient given that innovation in the digital age is increasingly dependent on employee's ability to leverage AI insights, tool and platforms to avoid repetition and solve complex problems, co-create value and deliver smart solutions [4].

In similar vein, the presence of structured *AI-training programs* within organizations is becoming a pivotal mechanism through which employees build the competencies required to engage effectively with AI technologies. These programs not only enhance technical skill sets but also cultivate a mindset conducive to experimentation and continuous learning — a key attribute of innovative work behavior. Despite this, there remain a dearth of empirical studies investigating the mediating role of AI-specific training in translating AI-supported leadership into tangible innovation outcomes at the individual level. Furthermore, this study employed organizational innovative climate (OIC) as a boundary condition which refer to a "*shared perception among employees about the contextual factors that support organizational innovation*" [5]. However, the interaction between AI-supported leadership, AI training and innovative climate remains under-theorized. Specifically, how such climates reinforce or moderate the effects of AI supported leadership interventions on employees IWB is still unclear in extant literature [4]. This study is grounded in COR theory by Hobfoll, *et al.* [6], which posits that individuals are more motivated to acquire, maintain and utilize resources to cope with stress and achieve values goals. Applying this lens, we conceptualize AI supported leadership, AI-training programs and OIC as critical organizational resources that jointly influence employees' AI-driven IWB. AI leadership offers cognitive and technological support, trainings to enhance the employee competence, and a supportive climate reinforces the utilizes of both.

Despite the conceptual relevance of this study's construct, existing research has largely examined them in isolation, with limited integrative models explaining their joint effects on innovation behavior in AI-driven workplaces. This study addresses this gap by developing a mechanism on a relationship of above-mentioned constructs and test it empirically. By elucidating these relationships, this study contributes to the emerging discourse on AI-enabled organizational transformation, offering both theoretical insights and practical guidance for leveraging AI as a leadership and innovation enabler. The findings are particularly relevant for high-tech industries undergoing rapid digital transformation, where human-AI collaboration is becoming central to organizational competitiveness and innovation capacity.

2 Theory and Hypotheses

Despite growing scholarly attention toward the organizational applications of AI, researchers continue to face challenges in explicating how AI-enabled leadership practices influence employee level innovative behaviors. To establish a robust theoretical foundation for this study, we draw on the COR theory of [6], which posits that individuals strive to acquire, retain and protect valuable resources to achieve optimal functioning and performance outcomes [7]. In organizational settings, resources are not limited to material assets but also include cognitive, social and contextual factors that empower individuals to adapt, perform and innovate in response to evolving demands [8]. Within this framework, AI-supported leadership can be viewed as a strategic resource that provides employees with both cognitive and technological support necessary for enhancing their capacity to engage in AI-driven IWB [9].

AI-supported leadership refers to the strategic incorporation of AI tools for instance predictive analytics, machine learning algorithms and decision-support system into leadership processes to enhance data-driven decision making, empowers employees and deliver context sensitivity guidance [1]. However, several studies on supportive style of leadership across the fields, researchers for instance [10], stated that such supportive leadership style fosters an environment where information accessible, decision are transparent and strategic direction is responsive based on situation. By leveraging AI, leaders are better equipped to provide timely feedback, clarify expectations and allocate resources efficiently which critical in reducing role ambiguity and cognitive overload [11]. Drawing from the COR theory, leadership practices that offer cognitive and technological resources contribute to employee's psychological safety and perceived control, thereby reducing workload, perceived threats and motivational strains. When employees feel supported and empowered through AI – supported leadership, they are more likely to engage in proactive creative behaviors that go beyond routine repetitive task and performance hallmarks of AI-driven IWB [9]. In this context, AI-supported leadership function as both a resource generator and an enabler of employee innovation by fostering condition conducive to experimentation, risk-taking and continuous learning. Hence, we propose that:

H1: AI-supported leadership is positively associated with employees' AI-driven IWB.

AI-supported not only empowers employees through data driven decision-making personalized managerial support but also plays a critical role in fostering the infrastructure necessary for continuous workforce upskilling, in AI-intensive environment [12]. As organization increasingly develop digital fluency and technical competencies to interact effectively with these intelligent systems [2, 13]. Leaders who are adeptly integrate AI-tools into their leadership practices are more likely to recognize skill gaps within their teams and proactively advocate for targets, forward looking AI-training programs [14, 15]. These programs may serve as a critical mechanism to build an employees' technical capabilities, foster adaptive learning mindsets and enhance their ability to co-create value alongside AI system in innovation-driven roles [16]. From COR theory standpoint AI-supported leadership operated as proactive and strategic resource-conserving force. By initiating and supporting training interven-

tions, such leadership mitigates potential resources losses-such as technical anxiety, digital skill gap and knowledge obsolescence ^[1]. Accordingly, AI-supported leadership is expected to be a key antecedent of the institutionalization of AI-training programs within organizations. Therefore, it is proposed that:

H2: AI-supported leadership is positively associated with AI-training programs.

AI-trainings programs have become essential in equipping employees with the skills and cognitive readiness to thrive in increasingly AI-augmented work environments. These programs are not merely technical upskilling initiatives; rather they serve as strategic enabler of innovation by fostering employees' confidence and competence in leveraging AI tools for problem-solving creative ideation and process improvement ^[2, 4]. As organization invest in AI-driven transformation employees to shift from passive technology users o achieve co-creator of value^[16]. In this vein the researchers for instance Wamba-Taguimdje, *et al.* ^[13], stated in their study that digital transformation required literacy of algorithmic thinking and adaptability / competencies that are effectively through structure, future-focused AI-training initiatives. From COR theory perspective, AI-training programs function as a resource augmenting mechanism, enabling employees to require critical knowledge and psychological resources needed to navigate technological change. Therefore, Jarrahi ^[1] stated that reducing technological related uncertainty and enhancing perceived self-efficacy, these programs minimize potential resources losses; for instance, cognitive workload, digital fatigue or resistance to innovation. When employees feel confidently trained and supported they are more likely to engage in risk-taking, experimentation and creative problem solving all of which characterizing AI-driven IWB. Thus, it is proposed that:

H3: AI-training programs. is positively associated with AI-driven IWB.

However, the mere presence of AI-supported leadership does not automatically translate into higher innovation outcomes unless employees are adequately trained and prepared to operationalize AI technologies into their routine tasks. According to the Kambur and Akar ^[17] stated that it is certainly difficult for individual to understand the knowledge and to apply it, hence there is required to provide certain trainings. AI-training programs serve as a critical resource acquisition process that enhances employees' competence and confidence in utilizing AI tools effectively ^[9, 18]. Such structured training efforts enabled the internationalization of AI related knowledge, foster digital fluency and create opportunities for experimentation thereby acting as a bridge between leadership direction and behavioral execution ^[4, 9, 17]. COR theory suggests that when employees are provided with new or enriched resources i.e. (skills development) program, they are more likely to conserve, protect and invest those resources toward high value of outcomes like innovation^[19]. Thus, it proposed that:

H4: AI-training programs mediate the relationship between AI-supported leadership and employees' AI-driven IWB.

While leadership support and trainings are vital, the effectiveness if often shaped by broader organizational condition. In line with COR theory's contextual sensitivity, this study considers organizational innovative climate as a higher order enabling resources that amplifies the effects of leadership and training on innovation

behavior. An innovative climate reflects a shared perception that creativity and experimentation are encouraged, supported and rewarded within the organization [5]. When individual operate in such climates, they are more likely to invest their personal and job resources-such as acquired skills and leadership support into innovative efforts, knowing that organizational context is conducive to innovate^[20]. Therefore, OIC is posited to strengthen both the direct and indirect paths from AI-supported leadership to AI-driven IWB. Thus, it is proposed that:

H5: OIC positively moderates the relationship between AI-supported leadership and AI-driven IWB, such that the relationship is stronger when innovative climate is high.

H6: OIC positively moderates the relationship between AI-supported leadership and AI-training programs, such that the relationship is stronger when innovative climate is high

H6: OIC positively moderates the relationship between AI-training programs and AI-driven IWB, such that the relationship is stronger when innovative climate is high.

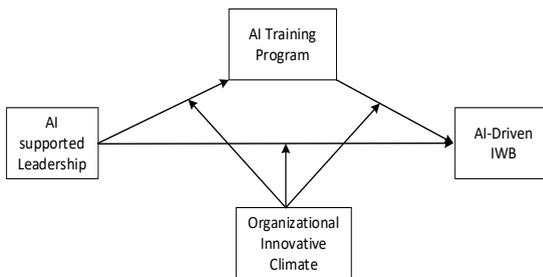


Fig:1 Research Model

Together, this theoretical model captures a multi-level, resources-based explanation of high AI-supported leadership practices influence employee's innovation in AI intensive environments. By situating leadership training and climate as interrelated organizational resources, the study contributes to a more integrated understanding of the psychological and contextual condition under which AI technologies enhance human innovation potential.

3 Methods and Materials

This study comprised middle and top-level management working in different departments at high-tech organizations in Russia. These organizations are selected based on their existing in high-technological products and services recognized by Russian government with their technological initiatives. During the data collection procedure, the authors implemented all the necessary measures to protect the privacy of respondents. Moreover, the anonymity of the respondents was kept by ensuring

them that their information would not be made public by any means to any external body.

The survey instrument of this study consists of two parts. The first part gathered demographic information from participants, encompassing age, gender, and experience. The subsequent section gauged the constructs of variables using a seven-point Likert-type scale ranging from (1 = highly disagree to 7 = highly agree). To meet the study's requirements, measures from earlier research were utilized and modified. This includes a **6-item** measurement scale of AISL from He, *et al.* [21]. The **7-items** scale to measure AI-training programs was adapted from [22]. AI-driven IWB was measured by adopted version of originally developed scale of **6-item** by [23]. The OIC measured by **4-items** scales adopted from [24]

Table 1. Demographics of Respondents (N=321)

Variable	Categories	Frequency	Percentage	Variable	Categories	Frequency	Percentage
Gender	Male	185	57.6	Experience	1-5 years	84	26.2
	Female	136	42.4		6-10 years	97	30.2
Age	≤ 25	67	20.9		11-15 years	96	29.9
	26-30	64	19.9		16-20 year	35	10.9
	31-35	59	18.4		21 above years	9	2.8
	36-40	57	17.8				
	≥ 41	74	23.1				

A total of 369 survey questionnaire was distributed to top and middle-level managers, yielding 348 response. Following data cleaning and screening, 27 incomplete response were excluded, resulting valid 321m responses. Common method bias is a concern when both the dependent and independent variables are measured from the same individual. Harman’s single-factor test was conducted in SPSS using **23-item** loadings to assess this . The results indicated that a single factor accounted for only 32.549% of the total variance, which is well below the 50% threshold, suggesting minimal bias. Furthermore, the study employed the full collinearity technique, as recommended by [25], by treating all latent variables as outcome variables and calculating variance inflation factor (VIF) values. Consistent with Kock [25] findings, all VIF values were below the threshold of 3.3, confirming the absence of significant method bias.

4 Results

The analysis in this research is divided into two phases. In the first phase, the measurement model including reflective constructs was checked based on their validi-

ty and reliability. Then, the main hypothesized model was tested using a structural model in the second phase.

4.1 Measurement

The consistency and authenticity of the constructs were assessed using composite reliability, and Cronbach's alpha following the guidelines of Hair, *et al.* [26]. The results are in **Table 2**. Indicates that both Cronbach's alpha and CR values exceeded the > 0.70 threshold, confirming the reliability and internal consistency of the constructs. Additionally, the average variance extracted (AVE) values were all above >0.50 , demonstrating the convergent validity of the constructs. [26].

Table 2. Outer loadings, reliability, and validity

Variables	items	Avg. loading	Cronbach's (α)	CR	AVE
AI-Supported Leadership	6	0.892	0.913	0.921	0.713
AI-training Programs	7	0.855	0.883	0.852	0.652
AI-driven Innovative Work Behavior	6	0.794	0.862	0.833	0.633
Organizational Innovative Climate	4	0.796	0.912	0.928	0.562

Note: Each latent construct's convergent validity was established by calculating the average variance explained, or AVE.

Furthermore, the discriminant validity in the table was also assessed by using the HTMT ratio and the Fornell-Larcker criterion. The HTMT ratio remained at the 0.85 thresholds reported in **Table 3**, confirming the discriminant validity. Similarly, Fornell and Larcker [27] approach showed that the square root of AVE values (bold diagonal) exceeded bivariate correlations, further ensuring discriminant validity.

Table 3. Zero-order correlations and discriminant validity

Variable Name	AI-SL	AI-TP	AI-IWB	OIC
AI-Supported Leadership	0.841	0.521**	0.654**	0.322**
AI-training Programs	0.658**	0.872	0.660**	0.212**
AI-driven Innovative Work Behavior	0.695	0.561**	0.881	0.255**
Organizational Innovative Climate	0.312	0.388	0.322	0.841

Note: Correlations are significant at 1%, i.e., ** $P < 0.01$ level. Bold values are the squared root of AVE. Zero-order correlations (above the bold) and HTMT (bold)

4.2 Hypotheses Testing

The SEM model in SPSS, employing the bias-corrected percentile method with 5000 bootstraps was used to test hypotheses. The results reveal that AISL significantly influenced AI-driven IWB ($\beta = 0.347$; BootSE = 0.048; CIs at 95% 0.322 and 0.634). Similarly, AISL has a direct and significant influence on AITP ($\beta = 0.487$; BootSE = 0.062; CIs at 95% 0.412 and 0.634) and AITP has significant effect on AI-driven IWB ($\beta = 0.321$; BootSE = 0.056; CIs at 95% 0.219 and 0.364). The mediating effect of AITP is also significant ($\beta = 0.343$; BootSE = 0.062; CIs at 95% 0.315 and 0.449). Hence all the direct and indirect hypotheses are accepted. Moreover, the moderating effect of OIC on the AISL and AI-driven IWB link is significant ($\beta = 0.312$; BootSE = 0.073; CIs at 95% 0.0483 and 0.623). Moderating effects of OIC on AISL-AITP relationship also find significant with the effects of ($\beta = 0.412$; BootSE = 0.061; CIs at 95% 0.219 and 0.457). OIC moderating effects on AITP and AI-driven IWB relationship also found significant with the effects of ($\beta = 0.417$; BootSE = 0.051; CIs at 95% 0.418 and 0.578). Thus, all the proposed hypotheses are accepted (**Refer to Table 4.**)

Table 4. Direct, indirect, and moderation (Standardized effects)

	Est (β)	S E	T- value	P- value	U LCI	L LCI	Status
Direct Effect							
AISL → AI-IWB	0.347	0.048	7.229	0	0.322	0.634	Accepted
AISL → AITP	0.487	0.062	7.855	0	0.412	0.634	Accepted
AITP → AI-IWB	0.321	0.056	5.732	0	0.219	0.364	Accepted
Mediating Effect							
AISL → AITP → AI-IWB	0.343	0.062	5.532	0	0.315	0.449	Accepted
Moderating Effect							
AISL*OIC → AI-IWB	0.312	0.073	4.274	0.026	0.0483	0.623	Accepted
AISL*OIC → AITP	0.412	0.0613	6.721	0	0.219	0.457	Accepted
AITP*OIC → AI-IWB	0.417	0.0519	8.035	0	0.418	0.578	Accepted
<i>Adjusted R2</i>				For AITP = 0.357			For AI-IWB = 0.526

Note: AISL: AI-Supported Leadership; AITP: AI-training program; AI-IWB, AI-driven Innovative Work Behavior; OIC: Organizational Innovative Climate

5 Conclusion

This study investigates the multifaceted role of AI-supported leadership in fostering AI-driven IWB among employees, with a particular emphasis on the mediating effects of AI-training programs and the moderating influence of an OIC. Drawing on COR theory, the finding confirms that AI-supported leadership acts as a vital enabler of innovation by equipping employees with both technical competencies and psychological resources. Its influence is strengthened through structured training programs that develop employees' digital fluency and through organizational climate that encourage experimentation and adaptability. The study highlights that leadership effectiveness in AI-integrated environments depends not only on technical adoption but also on a proactive approach to workforce development. When aligned with AI-training initiatives and supported by a culture of innovation, leadership facilitates a work environment where AI tools are actively leveraged for creative problem solving and continuous improvement.

The insights offer practical implications for leaders and decision-makers integrated AI within leadership practices, investing in targeted upskilling and fostering innovation-centric culture are essential for building and future-ready organizations. By articulating the pathways through which leadership, training, and climate interact to enhance AI-driven innovation, this research contributes to the evolving literature on digital transformation and organizational behavior. Future research may explore these dynamics across industries, cultural context, or assess their long-term impact on organizational performance.

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