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Supervisory Coaching Leadership and Employee Innovation: AI Literacy and Organizational Support Effects

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Abstract

This study examined the relationships among supervisors' coaching leadership, AI literacy, AI-contextualized perceived organizational support (AI-POS), and employees' innovative behavior in South Korean small and medium-sized enterprises (SMEs). Using PLS-SEM with data from 429 employees, coaching leadership showed a strong association with AI literacy ($\beta = .397$, $p < .001$), while its direct association with innovative behavior was modest ($\beta = .096$, $p = .047$). Approximately 72.9% of the total effect of coaching leadership on innovative behavior was transmitted indirectly through AI literacy (indirect effect $\beta = .258$), indicating that coaching leadership functions primarily as an enabler of AI competency development rather than a direct driver of innovation. AI literacy exhibited the strongest association with innovative behavior ($\beta = .649$, $p < .001$). CFA results revealed that the instrumental and psychological support dimensions of AI-POS were empirically non-separable (inter-factor correlation = 1.000), and a unified AI-POS composite was therefore adopted as the primary moderator. AI-POS significantly moderated the AI literacy–innovative behavior relationship ($\beta = .181$, $p < .001$), suggesting that organizational AI support strengthens the conversion of AI competency into innovative behavior. Sub-dimension analyses were treated as exploratory given extreme inter-correlations among coaching leadership sub-dimensions ($r = .929$–$.940$, VIF > 10). These findings extend coaching leadership theory and the AMO framework to the AI context.

Keywords : Supervisors' Coaching Leadership, AI literacy, Innovative Behavior, Perceived Organizational Support, Small and Medium-sized Enterprises

JEL Classification Code : M12, M53, O31, O33, D83

1. Introduction[1]

The rapid proliferation of generative AI technology is creating new competency demands for organizational members. AI is no longer a tool exclusive to IT specialists but has become an everyday work tool that all employees are expected to utilize (Southworth et al., 2023). As the critical resource for innovation has shifted from physical capital to data, algorithms, and knowledge, innovative behavior is being redefined as the act of redesigning the collaborative interface between humans and AI (Holm et al., 2023). The introduction of AI automates repetitive tasks and repositions the human role toward higher-order domains such as problem definition, insight generation, and ethical judgment (Brem et al., 2021; Cimino et al., 2024). Within this context, AI literacy—the competency to effectively understand and utilize AI—is emerging as a novel antecedent of innovative behavior.

SMEs constitute 99.9% of all enterprises and account for 80.4% of total employment in South Korea (Ministry of SMEs and Startups, 2025), yet their AI adoption levels remain considerably lower than those of large corporations. Insufficient financial resources, specialized personnel, and IT infrastructure represent the primary barriers. According to the resource-based view (Barney, 1991), in environments with constrained physical resources, employee competencies become an increasingly critical source of competitive advantage. In SMEs, AI literacy can function as a core competency that compensates for the shortage of specialized personnel, substantiates the effectiveness of technology adoption by verifying, calibrating, and interpreting AI outputs, and manages ethical and regulatory risks.

Against this backdrop, increasing scholarly attention is being directed toward leadership factors that promote employees' AI literacy. Coaching leadership, as a leadership style that fosters the development of employees' potential and autonomous learning (Whitmore, 1992), may contribute to AI literacy development through vicarious learning and the strengthening of AI self-efficacy grounded in social cognitive theory (Bandura, 1986), as well as through the enhancement of intrinsic motivation anchored in self-determination theory (Deci & Ryan, 2000). Jeong and Jeong (2025) empirically demonstrated that coaching leadership serves as a key leadership factor that moderates the relationship between AI adoption and job reflection. However, research examining the direct influence of coaching leadership on AI literacy remains at an early stage; existing studies have primarily focused on transformational or digital leadership (Kim, 2025), and investigations linking coaching leadership to literacy have been limited to the digital literacy level (Kim & Oh, 2023).

Furthermore, AI literacy does not invariably translate into innovative behavior. Technostress-induced role overload or a deep understanding of AI that paradoxically triggers conservative behavior can render this relationship context-dependent. Consequently, how organizations support employees' AI utilization constitutes an important boundary condition. The present study introduces the novel concept of AI-contextualized perceived organizational support (AI-POS) and explores how instrumental support perceptions (provision of AI tools, training, and budgets) and psychological support perceptions (tolerance for failure and encouragement of experimentation) differentially moderate the relationship between AI literacy and innovative behavior.

Building on the above discussion, this study pursues five specific objectives. First, the direct associations of coaching leadership with innovative behavior and AI literacy are examined. Second, the study investigates whether AI literacy functions as an antecedent of innovative behavior. Third, the mediating role of AI literacy in the coaching leadership–innovative behavior relationship is tested. Fourth, the moderating role of AI-POS and the conditional indirect association on the AI literacy–innovative behavior relationship are examined. Fifth, the study explores which sub-dimensions of coaching leadership exert differential effects on AI literacy.

The theoretical significance of this study lies in establishing a novel pathway connecting coaching leadership and AI literacy, delineating the boundary condition role of AI-POS, and exploring innovation mechanisms within the SME context. The study employs culturally validated Korean measurement instruments—the Korean Stowell-based Coaching Leadership Scale (K-SCLS; Lee, 2025) and the Korean Generative AI Literacy Scale (Noh et al., 2024)—thereby moving beyond simple translations of Western instruments to ensure cultural validity. In practical terms, the findings are expected to provide SME managers with guidance on leadership development priorities for the AI era and to offer insights for designing AI literacy training programs.

2. Literature Review

2.1. Coaching Leadership and Innovative Behavior

Coaching leadership refers to a leadership behavior in which leaders, grounded in trust in employees' potential and capabilities, establish horizontal partnership relationships and, through dialogue, feedback, and motivation, support employees in setting their own goals and solving problems, thereby simultaneously promoting individual growth and organizational performance (Joh, 2024). Coaching leadership represents the application of pure coaching principles to organizational contexts and possesses an intersecting character between coaching and leadership (Joh, 2024). The present study employed the K-SCLS developed by Lee (2025), measuring coaching leadership across four sub-dimensions: direction setting, performance evaluation, competency development, and relationship building. The K-SCLS was developed to reflect culturally specific Korean mechanisms such as jeong (affection), uri consciousness (we-ness), and chemyeon (face-saving), exhibiting a balanced hierarchical structure in which a strong general factor coexists with meaningful sub-dimensions (ECVH = 58.2%).

Innovative behavior is defined as a series of voluntary and intentional actions through which organizational members generate novel ideas for improving their work or organizational performance, promote these ideas to secure support, and implement them in actual practice (Janssen, 2000; Scott & Bruce, 1994). Unlike creativity, which focuses on idea production, innovative behavior is an action-oriented concept encompassing adoption and implementation (Anderson et al., 2014), and it possesses the character of extra-role behavior that extends beyond formal job requirements.

Prior research has consistently reported that coaching leadership is significantly and positively associated with employees' innovative behavior. Jo (2024) confirmed that direction setting and performance evaluation directly and positively influenced innovative behavior in SMEs, and Kim and Oh (2023) reported that coaching leadership had a significant positive effect on innovative behavior. From the perspective of the Ability-Motivation-Opportunity (AMO) model, coaching leadership simultaneously promotes ability enhancement through feedback and learning opportunities, motivation strengthening through achievement and relationship improvement, and opportunity expansion through change and innovation participation (McCarthy & Milner, 2019). Based on this discussion, the following hypothesis is proposed:

Hypothesis 1. Supervisors' coaching leadership is positively associated with employees' innovative behavior.

2.2. Coaching Leadership and AI Literacy

AI literacy refers to the complex competency of identifying and understanding AI, and utilizing AI devices and services with ethical and critical attitudes to perform creative output and social interaction (Long & Magerko, 2020; Hwang & Hwang, 2023). This construct extends beyond simple technological usage ability to encompass a multidimensional structure integrating critical thinking, ethical judgment, and creative problem-solving (Ng et al., 2021).

To clarify the conceptual scope of AI literacy, it is necessary to delineate its boundaries relative to two adjacent constructs: digital literacy and technology acceptance. First, regarding conceptual nature, technology acceptance—as operationalized through the Technology Acceptance Model (TAM; Davis, 1989)—centers on motivational constructs such as perceived usefulness and perceived ease of use that predict adoption intention; it is fundamentally an attitudinal-intentional construct concerned with whether individuals will use a technology. Digital literacy concerns the operational competency to use deterministic digital tools for information retrieval and content creation. In contrast, AI literacy is a competency construct that encompasses the ability to interact with probabilistic and nondeterministic systems whose outputs are inherently uncertain and context-dependent. Second, AI literacy requires domain-specific competencies that have no parallel in digital literacy or technology acceptance: the ability to detect algorithmic bias, hallucination, and opacity; the capacity for ethical judgment regarding AI-generated content; and the skill to leverage generative AI as a collaborative partner for novel problem-solving rather than merely as an information retrieval tool (Noh et al., 2024; Hwang & Hwang, 2023). Third, whereas technology acceptance models predict a dichotomous outcome (adopt vs. not adopt) and digital literacy implies a continuum of tool proficiency, AI literacy integrates cognitive (understanding AI mechanisms), evaluative (critical assessment of AI outputs), ethical (responsible use), and creative (generative collaboration) dimensions into a unified competency that enables qualitatively different human-technology interaction.

These conceptual distinctions are empirically supported in the present data. Confirmatory factor analysis comparing alternative measurement models revealed that a single-factor model for AI literacy demonstrated excellent fit (CFI = .999, TLI = .999, RMSEA = .017, SRMR = .009), and a four-factor correlated model yielded inter-factor correlations ranging from .994 to 1.002, indicating near-complete empirical convergence. A chi-square difference test confirmed that the four-factor model did not significantly improve upon the single-factor model ($\Delta\chi^2$ = 1.53, df = 6, p = .958). This pattern indicates that while the four sub-dimensions—AI utilization ability, critical evaluation, ethical use, and creative application—are theoretically distinguishable facets, they empirically function as an integrated competency driven by a strong general factor. This finding justifies the use of the composite AI literacy score in the mediation analysis and suggests that the strong association with innovative behavior (β = .649) reflects the synergistic operation of complementary competency facets rather than the independent contribution of any single sub-dimension.

The present study measured AI literacy using the Korean Generative AI Literacy Scale developed by Noh et al. (2024), comprising four sub-dimensions: AI utilization ability, critical evaluation, ethical use, and creative application.

The influence of coaching leadership on AI literacy is supported by two theoretical foundations. First, from the perspective of social cognitive theory (Bandura, 1986), the process by which coaching leaders demonstrate AI utilization and provide feedback promotes vicarious learning and strengthens employees' AI self-efficacy. Second, from the perspective of self-determination theory (Deci & Ryan, 2000), coaching leadership satisfies the basic psychological needs for autonomy, competence, and relatedness, thereby enhancing intrinsic motivation, which in turn leads to voluntary AI learning. Given that only 21.9% of SMEs in the present sample possessed formal AI training programs, supervisors' coaching may function as a critical learning pathway that supplements or substitutes for formal training.

Empirically, Kim and Oh (2023) confirmed that coaching leadership had a significant positive effect on digital literacy, and Jeong and Jeong (2025) demonstrated that coaching leadership served as a key leadership factor moderating the relationship between AI adoption and job reflection. However, research directly examining the effect of coaching leadership on AI literacy remains limited, underscoring the expected empirical contribution of the present study.

Hypothesis 2. Supervisors' coaching leadership is positively associated with employees' AI literacy.

2.3. AI Literacy, Innovative Behavior, and Mediation

Innovative behavior in the AI era demands complex competencies involving understanding and leveraging AI technology to improve work processes and enhance organizational performance. According to Gama and Magistretti (2025), AI promotes innovation through three functions—replace, reinforce, and reveal—and critical AI literacy serves as a prerequisite for effectively leveraging these functions. AI utilization ability supports operational efficiency and the discovery of hidden patterns; critical evaluation enables the recognition of errors and biases in AI outputs and the development of refined innovative ideas; ethical use promotes sustainable innovation; and creative application supports approaching problems from novel perspectives. In this regard, Ji et al. (2025) reported that AI literacy had a significant effect on innovative behavior through the mediation of psychological need satisfaction and creative self-efficacy.

Hypothesis 3. AI literacy is positively associated with employees' innovative behavior.

The influence of coaching leadership on innovative behavior is likely transmitted through employees' competency development. According to the triadic reciprocal causation model of social cognitive theory (Bandura, 1986), the pathway through which environmental factors (coaching leadership) influence behavioral outcomes (innovative behavior) via cognitive and competency changes (AI literacy) is theoretically predicted. From the perspective of absorptive capacity theory (Zahra & George, 2002), coaching leadership functions as a facilitating factor that transforms potential absorptive capacity (acquisition and assimilation of AI knowledge) into realized absorptive capacity (transformation and exploitation of AI knowledge), with AI literacy serving as the mediating mechanism in this conversion. Empirically, Kim and Oh (2023) confirmed partial mediation in the coaching leadership → digital literacy → innovative behavior pathway, and Kim (2025) identified a mediation effect in the digital leadership → digital literacy → innovative behavior pathway.

Hypothesis 4. AI literacy mediates the relationship between coaching leadership and innovative behavior.

2.4. Moderating Effect and Moderated Mediation of AI-Contextualized Perceived Organizational Support

The present study proposes AI-contextualized perceived organizational support (AI-POS) as this opportunity factor. AI-POS is defined as "the degree to which employees perceive that their organization values the development of AI literacy and AI utilization performance and provides the necessary resource-based and emotional support for these purposes." This represents a novel concept that adapts traditional perceived organizational support (Eisenberger et al., 1986) specifically for the AI context.

Conceptually, AI-POS encompasses two distinguishable facets: instrumental support (perceived provision of tangible resources such as AI tools, training, time, and budgets) and psychological support (perceived emotional support such as tolerance for failure, encouragement of experimentation, and recognition of achievements). From conservation of resources theory (Hobfoll, 1989), instrumental support provides directly proximal resources that create concrete behavioral possibilities for AI-enabled innovation. From psychological safety theory (Edmondson, 1999) and social exchange theory (Blau, 1964), psychological support cultivates an environment in which employees feel safe to experiment with AI and are motivated to reciprocate organizational support through innovative behavior. However, it is acknowledged a priori that these two facets may be difficult to separate empirically, particularly with short subscales, given that both tap a common higher-order perception of organizational support in the AI domain. Accordingly, the primary hypothesis concerns the moderating effect of AI-POS as a unified construct, while dimension-level differential effects are treated as an exploratory research question.

Hypothesis 5. AI-POS positively moderates the relationship between AI literacy and innovative behavior, such that the positive association between AI literacy and innovative behavior is stronger when AI-POS is higher.

Research Question 2 (Exploratory). Do the instrumental support and psychological support dimensions of AI-POS exhibit differential moderating effects on the AI literacy–innovative behavior relationship?

Furthermore, to examine whether the moderating effect operates across the entire mediation pathway, moderated mediation effects are analyzed (Hayes, 2018). It is predicted that higher levels of instrumental or psychological support will strengthen the indirect effect of coaching leadership on innovative behavior through AI literacy.

However, theoretical considerations suggest that the moderating effect of psychological support may be weaker than that of instrumental support, or may fail to reach significance, for at least three reasons. First, from a job demands–resources perspective (Bakker & Demerouti, 2017), organizational resources differ in their proximity to the focal behavior. Instrumental support provides resources that are directly proximal to AI-enabled innovation—tools, training time, and budget that create immediate behavioral possibilities. Psychological support, by contrast, provides distal, affective resources whose primary function is to reduce threat appraisal and anxiety. Drawing on conservation of resources theory (Hobfoll, 1989), once a baseline level of psychological safety is established, additional increments may yield diminishing returns for behavioral activation, whereas each additional unit of instrumental resource opens a concrete new avenue for action. Thus, psychological support may operate more as a necessary but insufficient condition—its absence impedes the conversion of AI literacy into innovative behavior, but its presence beyond a threshold level may not actively amplify this conversion. In contrast, the provision of tangible AI tools, training time, and budget—instrumental support—may function more as a motivating factor that directly enables new behavioral possibilities. Second, the psychological safety mechanism that underlies psychological support may already be captured in the first half of the mediation chain through the relationship-building dimension of coaching leadership. If relationship building fosters psychological safety that facilitates AI literacy acquisition, then the incremental contribution of organizational-level psychological support to the subsequent AI literacy → innovative behavior conversion may be limited. Third, given the anticipated high inter-correlation between instrumental and psychological support dimensions (both tapping AI-specific organizational support), the unique variance of psychological support may be substantially absorbed when both are entered simultaneously, potentially suppressing the moderation coefficient. For these reasons, although Hypothesis 6 proposes a positive moderating effect of psychological support, the theoretical expectations are weaker compared to Hypothesis 5, and the possibility of nonsignificance is acknowledged a priori.

Hypothesis 6. The indirect effect of coaching leadership on innovative behavior through AI literacy is moderated by AI-POS, such that the indirect effect is stronger when AI-POS is higher (moderated mediation).

Research Question 3 (Exploratory). Do the instrumental and psychological support dimensions of AI-POS differentially moderate the indirect effect of coaching leadership on innovative behavior through AI literacy?

2.5. Exploratory Research Question

The sub-dimensions of coaching leadership may exert differential effects on AI literacy. From the perspective of self-determination theory (Ryan & Deci, 2000), direction setting may create paradoxical tension between autonomy and control (Lee et al., 2020; Li et al., 2023), competency development may produce crowding-out effects through external intervention (Georgellis et al., 2011; Lohmann et al., 2016, 2018), and performance evaluation may undermine psychological safety (Edmondson, 1999; Kim et al., 2025). In contrast, relationship building is expected to contribute differentially to AI literacy by enhancing psychological safety and promoting learning behavior through high-quality interpersonal relationships (Carmeli et al., 2009; Frazier et al., 2017). However, given the anticipated high inter-correlations among coaching leadership sub-dimensions, estimation instability due to multicollinearity is a concern; thus, this investigation is approached as an exploratory research question rather than a confirmatory hypothesis.

Research Question 1. Do the sub-dimensions of coaching leadership (direction setting, performance evaluation, competency development, and relationship building) exert differential effects on the sub-dimensions of AI literacy?

The research model integrating the above hypotheses and research question is presented in Figure 1.

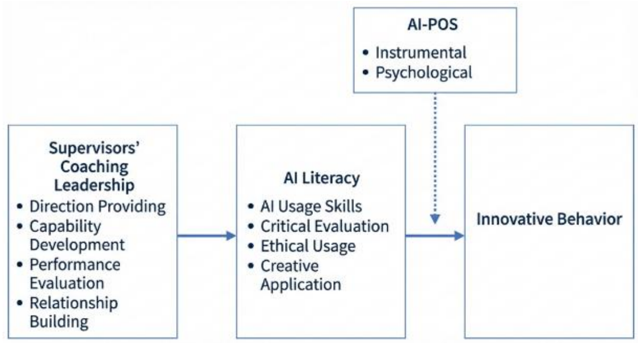

Figure 1: Research model

3. Methodology

3.1. Research Model

This study employed a moderated mediation model examining the influence of supervisors' coaching leadership (independent variable) on innovative behavior (dependent variable) through the mediation of AI literacy (mediator), while exploring the moderating effect of AI-POS (moderator) on the AI literacy–innovative behavior relationship. Specifically, the model comprised the following paths: the direct path from coaching leadership to innovative behavior, the path from coaching leadership to AI literacy, the path from AI literacy to innovative behavior, and the paths in which the two sub-dimensions of AI-POS (instrumental support perception and psychological support perception) each moderate the AI literacy–innovative behavior relationship. Gender, age, education level, and job rank were included as control variables.

3.2. Participants and Data Collection

The target population comprised employees of domestic SMEs (fewer than 300 full-time employees as defined by the Framework Act on SMEs) who had a direct supervisor and who either had experience using AI tools (e.g., ChatGPT, Claude, Copilot) or planned to use them in the future. Data were collected through an online panel provided by SPARK RESEARCH, a professional research firm, using a nonprobability sampling method over approximately two weeks from January 21 to February 7, 2026. Screening items were established to verify eligibility for survey participation, and quota sampling considering age group, industry sector, and company size was concurrently employed to ensure diversity in sample composition.

To mitigate common method bias arising from single-source self-report data, several procedural remedies were implemented following Podsakoff et al. (2003). Respondent anonymity was guaranteed, a cover statement encouraged honest responses by assuring that there were no right or wrong answers, and the measurement sequence was arranged so that the independent variable (coaching leadership), mediator (AI literacy), moderator (AI-POS), and dependent variable (innovative behavior) were separated by intervening scales and attention-check items designed to reduce consistency motives and create psychological distance between predictor and criterion measures.

Sample size was determined by comprehensively considering PLS-SEM requirements and model complexity. Hair et al. (2019) recommended that the minimum sample size for PLS-SEM be 10 times the maximum number of arrows directed at any endogenous construct. According to Cohen's (1992) statistical power analysis criteria, a sample of at least 200 participants is required to achieve 80% or greater power for detecting medium effect sizes. In moderation testing, where interaction term effect sizes tend to be smaller than main effects, a sufficiently large sample is particularly recommended. Considering these criteria comprehensively, the target was set at 400 or more valid responses after exclusion of careless responses. After excluding responses that failed to meet screening conditions, exhibited careless response patterns (consecutive identical selections, incorrect attention-check items), or contained excessive missing data, a final valid sample of 429 participants was obtained for analysis.

3.3. Measures

All measurement items were rated on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

Coaching leadership. Coaching leadership was defined as leadership behavior in which leaders, grounded in trust in employees' potential and capabilities, establish horizontal partnership relationships and, through dialogue, feedback, and motivation, support employees in setting their own goals and solving problems, thereby simultaneously promoting individual growth and organizational performance (Min, 2023; Do et al., 2023). The K-SCLS developed by Lee (2025) was adapted for the AI context. The K-SCLS addresses the citation errors and conceptual confusions in prior coaching leadership research raised by Joh (2021, 2022, 2024) while integrating Korean cultural specificity (ECVH = 58.2%). The scale consists of 16 items across four sub-dimensions: direction setting, performance evaluation, competency development, and relationship building. Cronbach's α for the sub-dimensions in the original scale ranged from .749 to .813.

AI literacy. AI literacy was defined as the integrated competency of understanding AI technology, critically evaluating it, using it ethically, and applying it creatively

(Noh et al., 2024). The Korean Generative AI Literacy Scale developed by Noh et al. (2024) was employed. The scale consists of 12 items across four sub-dimensions: AI utilization ability, critical evaluation, ethical use, and creative application. Cronbach's α for the sub-dimensions in the original scale ranged from .754 to .890.

Innovative behavior. Innovative behavior was defined as voluntary and intentional actions through which organizational members generate novel ideas for improving work or organizational performance, promote those ideas, and implement them (Janssen, 2000). The scale developed by Janssen (2000) and translated into Korean by Bu (2020) was used, comprising six items encompassing idea generation, idea promotion, and idea implementation. Cronbach's α for the original scale was .932.

AI-contextualized perceived organizational support. AI-POS was defined as the degree to which employees perceive that their organization values the development of AI literacy and AI utilization performance and provides the necessary resource-based and emotional support for these purposes. The perceived organizational support scale by Eisenberger et al. (1986, 1997) was modified for the AI technology context. The measure comprises six items across two sub-dimensions: instrumental support perception (perceived provision of tangible resources such as AI tools, training, and time) and psychological support perception (perceived emotional support such as tolerance for failure, encouragement of experimentation, and recognition of achievements). Given the absence of prior validation studies for AI-contextualized perceived organizational support scales, an exploratory approach was adopted in which the psychometric properties of the scale were systematically examined through measurement model evaluation. Because the AI-POS scale is newly adapted for the present study, its dimensional structure warrants particular scrutiny. Domestic research on perceived organizational support has consistently distinguished instrumental and psychological dimensions as conceptually separable facets (Kim, 2006; Park & Jang, 2015), and the present study follows this convention. However, given that the two dimensions share a common higher-order construct and are measured with only three items each, empirically high inter-correlations are anticipated. Accordingly, the measurement model evaluation section reports not only HTMT values but also the pattern of differential correlations with other constructs as supplementary evidence for discriminant validity.

Control variables. Gender, age, education level, and job rank were included as control variables to control for demographic variables that may influence innovative behavior. Additional demographic variables—tenure, company size, industry sector, and AI use experience and frequency—were collected to characterize the sample but were not entered as control variables in the path analysis to maintain model parsimony.

3.4. Analytic Strategy

Data analysis was conducted using SPSS 27.0 and SmartPLS 4.0. PLS-SEM was selected over CB-SEM for three methodological reasons. First, the research model includes a newly developed scale (AI-POS) that has not been previously validated; PLS-SEM's component-based estimation is recommended for models involving exploratory constructs because it does not require distributional assumptions and provides stable parameter estimates even when the nomological network is not fully established (Hair et al., 2019). Second, the model entails substantial complexity, including a mediated moderation structure with two moderators, interaction terms, and a sub-dimension level analysis with 16 simultaneous paths (four coaching leadership dimensions × four AI literacy dimensions); PLS-SEM handles such complexity with greater statistical power and fewer convergence issues than CB-SEM (Hair et al., 2017). Third, the primary objective of the structural model is prediction of the endogenous variables rather than confirmation of an established covariance structure, aligning with the prediction-oriented philosophy of PLS-SEM (Hair et al., 2019). Data analysis proceeded in a sequential procedure comprising preliminary analysis, measurement model assessment, common method bias assessment, and structural model testing.

In the preliminary analysis phase, frequency analysis and descriptive statistics were used to characterize the sample and examine the distributions of key variables, and normality was assessed through skewness and kurtosis. Following Kline's (2016) criteria, absolute values of skewness below 2 and absolute values of kurtosis below 7 were applied as thresholds.

In the measurement model assessment phase, SmartPLS 4.0 was used to systematically evaluate internal consistency reliability (Cronbach's α, rho_A, CR), convergent validity (factor loadings, AVE), and discriminant validity (HTMT ratio). Reliability thresholds were set at Cronbach's α and CR ≥ .70 (Nunnally & Bernstein, 1994), convergent validity thresholds at factor loadings ≥ .70 and AVE ≥ .50 (Hair et al., 2019), and the discriminant validity threshold at HTMT < .90 (Henseler et al., 2015). Common method bias was assessed through a combination of procedural remedies and statistical diagnostics, including the full collinearity VIF approach (Kock, 2015) and differential correlation pattern analysis.

Structural model testing was performed through 5,000 bootstrap replications. Main effects (Hypotheses 1–3) and the primary moderation effect (Hypothesis 5) were estimated using the two-stage approach, employing the unified AI-POS composite as the moderator; supplementary dimension-level moderation analyses (Research Question 2) were conducted using separate OLS regression models. Mediation (Hypothesis 4) was tested using bias-corrected 95% confidence intervals (BCa CI). Moderated mediation (Hypothesis 6) was examined using the unified AI-POS composite, with exploratory dimension-level moderated mediation reported as Research Question 3. Conditional indirect effects were computed at three levels of the moderator (mean ± 1 SD) and overall significance was evaluated using the index of moderated mediation (Hayes, 2018).

4. Results

4.1. Demographic Characteristics of Participants

The final sample comprised 429 valid respondents. Gender distribution was relatively balanced, with 236 males (55.0%) and 193 females (45.0%). The largest age group was 30–39 years (152, 35.4%), followed by 40–49 years (120, 28.0%), 20–29 years (95, 22.1%), and 50 years and older (62, 14.5%). Those with a four-year university degree or higher accounted for 79.4%. Job rank was relatively evenly distributed across assistant manager (124, 28.9%), manager (113, 26.3%), staff (111, 25.9%), and deputy manager or above (81, 18.9%). Company size ranged from fewer than 50 employees (136, 31.7%) to 200–300 employees (87, 20.3%), and industry sectors included services (142, 33.1%), manufacturing (138, 32.2%), IT/information and communications (75, 17.5%), distribution/logistics (43, 10.0%), and other (31, 7.2%).

Regarding AI-related characteristics, 87.6% of respondents reported AI tool use experience, and 68.0% used AI tools at least once per week. The proportion reporting their supervisor’s AI utilization level as moderate or above was 68.1%, and 78.8% reported having at least one AI-utilizing colleague on their team. Notably, 89.3% of supervisors were aged 40 or older. In contrast, only 21.9% reported the existence of a formal AI training program at their company, confirming that organizational-level AI competency development support remains insufficient in SMEs. This context suggests that supervisors’ coaching leadership may play a particularly critical role in employees’ AI literacy development where formal training infrastructure is absent.

4.2. Descriptive Statistics, Normality, and Correlations

The overall mean for supervisors' coaching leadership was 4.38 (SD = 0.91), exceeding the midpoint (4) on the 7-point scale. Among sub-dimensions, relationship building scored highest (M = 4.52, SD = 0.93), followed by competency development (M = 4.43, SD = 0.93), direction setting (M = 4.33, SD = 0.94), and performance evaluation (M = 4.22, SD = 0.93). The finding that relationship building scored highest reflects characteristics of Korean organizational culture that emphasize jeong (affection) and relational bonds, consistent with the K-SCLS development study (Lee, 2025).

The overall mean for AI literacy was 4.15 (SD = 1.00), slightly exceeding the midpoint. The four sub-dimension means ranged narrowly from 4.13 to 4.19, indicating that respondents perceived the various facets of AI literacy in a relatively balanced manner. Ethical use scored highest (M = 4.19, SD = 1.03), suggesting that awareness of ethical issues in AI use has formed, corroborating the discussion of Noh et al. (2024). The mean for innovative behavior was 3.96 (SD = 1.02), somewhat lower than other variables, reflecting the characteristic that this measure assesses the actual manifestation of behavior beyond the possession of perceptions or competencies.

For AI-POS, psychological support perception (M = 4.20, SD = 1.01) was higher than instrumental support perception (M = 3.85, SD = 1.00). The relatively lower instrumental support perception reflects the reality that tangible resource support such as AI tools, training, and budgets remains insufficient in SMEs, consistent with the low rate of formal AI training program availability (21.9%).

Normality assessment confirmed that all variables' skewness (−0.10 to 0.09) and kurtosis (−0.47 to 0.07) satisfied Kline's (2016) criteria (absolute skewness < 2, absolute kurtosis < 7), indicating no concerns regarding the normality assumption.

Examination of bivariate correlations revealed significant positive correlations between coaching leadership and AI literacy ($r = .396$, $p < .01$), between AI literacy and innovative behavior ($r = .635$, $p < .01$), and between coaching leadership and innovative behavior ($r = .340$, $p < .01$). For AI-POS, both instrumental support ($r = .165$, $p < .01$) and psychological support ($r = .126$, $p < .01$) exhibited significant positive correlations with innovative behavior, whereas their correlations with coaching leadership ($r = −.018$ to $.039$, mostly nonsignificant) and AI literacy ($r = −.107$ to $−.022$, mostly nonsignificant) were negligible. This differential pattern is consistent with the role of a moderator that is conceptually distinct from the independent and mediating variables yet maintains a meaningful relationship with the dependent variable. The inter-correlation between instrumental and psychological support was very high ($r = .928$, $p < .01$). Descriptive statistics, reliability coefficients, and bivariate correlations are presented in Table 1.

Table 1: Descriptive Statistics, Reliability, and Bivariate Correlations ($N = 429$)

Variable	Items	M	SD	α	CR	AVE	1	2	3	4	5
1. CL	16[a]	4.38	0.91	.926–.932[a]	.947–.952[a]	.817–.831[a]	—				
2. AIL	12[b]	4.15	1.00	.916–.925[b]	.947–.952[b]	.856–.870[b]	.396**	—			
3. IS	3	3.85	1.00	.923	.950	.865	.023	−.047	—		
4. PS	3	4.20	1.01	.926	.952	.869	−.007	−.078	.928**	—	
5. IB	6	3.96	1.02	.960	.968	.835	.340**	.635**	.165**	.126**	—

Note. CL = Coaching Leadership; AIL = AI Literacy; IS = Instrumental Support; PS = Psychological Support; IB = Innovative Behavior. [a] Range across four sub-dimensions (direction setting, performance evaluation, competency development, relationship building). [b] Range across four sub-dimensions (AI utilization ability, critical evaluation, ethical use, creative application). Below-diagonal entries are Pearson *r* values. Factor loading range: .898–.940. All HTMT values < .90 (range: .010–.854).
**$p < .01$.

4.3. Measurement Model Assessment

Following the PLS-SEM analysis procedure in SmartPLS 4.0, the measurement model was systematically evaluated for reliability, convergent validity, and discriminant validity prior to structural model testing (Hair et al., 2019).

Reliability and convergent validity. All indicator loadings across 11 latent variables ranged from .898 to .940, substantially exceeding the .70 criterion (Hair et al., 2019). Cronbach's α ranged from .916 to .960, Dijkstra-Henseler's rho_A (Dijkstra & Henseler, 2015) ranged from .916 to .964, and composite reliability (CR) ranged from .947 to .968, all exceeding the .70 threshold (Nunnally & Bernstein, 1994). AVE values ranged from .817 (performance evaluation) to .870 (AI utilization ability), substantially surpassing the .50 criterion proposed by Fornell and Larcker (1981), confirming that each latent variable explained more than 80% of the variance in its indicators.

Specifically, the coaching leadership sub-dimensions (direction setting: α = .932, CR = .952, AVE = .831; performance evaluation: α = .926, CR = .947, AVE = .817; competency development: α = .928, CR = .949, AVE = .822; relationship building: α = .928, CR = .949, AVE = .822), AI literacy sub-dimensions (AI utilization ability: α = .925, CR = .952, AVE = .870; critical evaluation: α = .924, CR = .952, AVE = .868; ethical use: α = .918, CR = .948, AVE = .859; creative application: α = .916, CR = .947, AVE = .856), AI-POS sub-dimensions (instrumental support: α = .923, CR = .950, AVE = .865; psychological support: α = .926, CR = .952, AVE = .869), and innovative behavior (α = .960, CR = .968, AVE = .835) all demonstrated excellent measurement quality. The AI-POS scale, newly adapted for the AI context based on Eisenberger et al.'s (1986, 1997) theoretical framework, exhibited particularly strong psychometric properties (factor loadings: .925–.935 for instrumental support, .930–.935 for psychological support), providing initial evidence that the theoretical structure translates appropriately to the AI domain.

Supplementary CFA for AI literacy dimensional structure. Because the theoretical contribution of this study rests partly on treating AI literacy as a unified mediator, the dimensional structure of the AI literacy scale was examined through CFA-based competing model comparisons using maximum likelihood estimation. As shown in Table 3, a single-factor model demonstrated excellent fit ($\chi^2 = 56.79$, df = 54, CFI = .999, TLI = .999, RMSEA = .017, SRMR = .009). A four-factor correlated model also fit well ($\chi^2 = 55.26$, df = 48, CFI = .999, TLI = .999, RMSEA = .019, SRMR = .008); however, the inter-factor correlations ranged from .994 to 1.002, and a chi-square difference test indicated no significant improvement over the single-factor model ($\Delta\chi^2 = 1.53$, df = 6, p = .958). A bifactor model with one general factor and four specific factors did not converge, further supporting the dominance of a single general factor. These results confirm that the four sub-dimensions function as a unitary competency in the present sample, supporting the use of the composite score in structural model testing.

Table 2: CFA Competing Model Comparisons for AI Literacy Dimensional Structure

Model	χ^2	df	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$ (vs. 1-factor)	p
1-factor	56.79	54	.999	.999	.017	.009	—	—

4-factor correlated	55.26	48	.999	.999	.019	.008	1.53 (df = 6)	.958
Bifactor	Did not converge	—	—	—	—	—	—	—

Note. N = 429. Maximum likelihood estimation. Inter-factor correlations in the 4-factor model ranged from .994 to 1.002.

Discriminant validity. Discriminant validity was evaluated using the HTMT ratio proposed by Henseler et al. (2015). All HTMT values ranged from .010 to .854, below the lenient threshold of .90. Although theoretically predictable levels of high correlations were observed among sub-dimensions belonging to the same higher-order construct (coaching leadership sub-dimensions: .841–.854; AI literacy sub-dimensions: .834–.842; AI-POS sub-dimensions: .844), all values met the criterion. Clear discriminant validity was confirmed between different higher-order constructs (coaching leadership–AI literacy: .211–.275; coaching leadership–innovative behavior: .181–.198; AI literacy–innovative behavior: .488–.500; AI-POS–other variables: .010–.117). In summary, the measurement model demonstrated adequate reliability, convergent validity, and discriminant validity.

A notable observation concerns the very high bivariate correlation between instrumental and psychological support ($r = .928$, $p < .01$), which raises a legitimate question about the empirical separability of the two dimensions. To address this concern rigorously, CFA-based competing model comparisons were conducted using maximum likelihood estimation.

As shown in **Table 4**, a single-factor model demonstrated excellent fit ($\chi^2 = 10.40$, df = 9, CFI = 1.000, RMSEA = .000, AIC = 4886.8). A two-factor correlated model also fit well ($\chi^2 = 10.13$, df = 8, CFI = 1.000, RMSEA = .015, AIC = 4888.6); however, the inter-factor correlation was estimated at 1.000, indicating complete empirical convergence. A chi-square difference test confirmed that the two-factor model did not significantly improve upon the single-factor model ($\Delta\chi^2 = 0.27$, df = 1, $p = .603$). These results indicate that, in the present sample, the distinction between instrumental and psychological support is not empirically supported despite its theoretical plausibility.

Table 3: CFA Competing Model Comparisons for AI-POS Dimensional Structure

Model	χ^2	df	CFI	TLI	RMSEA	AIC	$\Delta\chi^2$ (vs. 1-factor)	p
1-factor	10.40	9	1.000	1.000	.000	4886.8	—	—
2-factor correlated	10.13	8	1.000	1.000	.015	4888.6	0.27 (df = 1)	.603

Note. N = 429. Maximum likelihood estimation. Inter-factor correlation in the 2-factor model = 1.000.

These results carry direct implications for the structural model specification. Because the two AI-POS dimensions are empirically non-separable in the present sample (CFA inter-factor correlation = 1.000; $\Delta\chi^2 = 0.27$, df = 1, $p = .603$), the primary moderation analysis employs the unified AI-POS composite score (averaging all six items) as the moderator variable. This approach prioritizes construct validity over the theoretical two-dimension distinction and avoids collinearity-induced suppression effects that would otherwise compromise the interpretability of dimension-level coefficients. Supplementary analyses separately entering instrumental support and psychological support as sole moderators are reported to document the extent to which each dimension, in isolation, is capable of moderating the AI literacy–innovative behavior relationship. Collectively, these analyses address the core theoretical proposition—that organizational AI support strengthens the conversion of AI competency into innovative behavior (AMO framework)—while treating the differential importance of the two dimensions as an open empirical question requiring further investigation with more refined measurement instruments. Results (reported in Section 4.6.4) indicate that all three specifications yielded significant moderation, supporting the interpretation that organizational AI support as a whole—rather than one specific dimension—strengthens the AI literacy–innovative behavior conversion. The dimensional structure of AI-POS warrants further investigation in future research with expanded item pools and independent-sample validation. Given that this is the first application of an AI-contextualized POS scale, future studies should employ larger item pools, expert panel review, and independent-sample cross-validation to establish whether the two-dimensional structure replicates or whether a unidimensional AI-POS model provides a more parsimonious account.

4.4. Common Method Bias Assessment

Because all variables were measured through self-report from the same respondents at a single time point, the potential influence of common method bias (CMB) warrants careful evaluation (Podsakoff et al., 2003). The present study employed multiple diagnostic approaches; however, it is important to acknowledge at the outset that statistical diagnostics cannot definitively rule out CMB in a single-source cross-sectional design.

First, procedural remedies were implemented during data collection, including guaranteeing respondent anonymity, encouraging honest responses through a cover statement, and separating predictor and criterion measures with intervening scales and attention-check items (see Section 3.2).

Second, the full collinearity VIF approach recommended by Kock (2015) was applied. Inner VIF values for all predictor variables in the structural model were well below the 3.3 threshold indicative of CMB (AI literacy: VIF = 1.301; coaching leadership: VIF = 1.226), suggesting that artificial variance inflation attributable to common method was not substantial.

Third, CFA-based Harman's single-factor test revealed that a model constraining all 43 indicators to load on a single factor demonstrated severely poor fit (CFI = .456, RMSEA = .189), with the single factor accounting for only 38.8% of total variance. This pattern is inconsistent with a dominant method factor explanation.

Fourth, an unmeasured latent method construct (ULMC) analysis was conducted by adding a latent common method factor to the structural model. The core path from AI literacy to innovative behavior remained stable after controlling for the method factor (original $\beta = .621$; ULMC-adjusted $\beta = .607$; difference = .014), providing supplementary evidence that the key mediation pathway was not substantially inflated by shared method variance.

Fifth, the differential correlation pattern between AI-POS and the other constructs provides indirect evidence against uniform method-driven inflation. Despite being measured with the same method and at the same time point, AI-POS showed negligible correlations with coaching leadership ($r = -.018$ to .039) and AI literacy ($r = -.107$ to $-.022$, mostly nonsignificant), while exhibiting significant positive correlations with innovative behavior ($r = .126$–.165, $p < .01$). If CMB were inflating relationships uniformly, a consistent pattern of positive correlations across all construct pairs would be expected.

Taken together, these multiple diagnostics suggest that CMB did not substantially distort the core findings of this study. Nevertheless, it must be acknowledged that CMB cannot be entirely ruled out given the inherent limitations of a single-source, single-time-point design. All key variables—coaching leadership, AI literacy, and innovative behavior—are susceptible to social desirability bias, and shared method variance may have contributed to some degree of inflation in the observed relationships. This limitation is addressed further in Section 5.5, where specific recommendations for multi-source and longitudinal designs are provided.

4.5. Structural Model Assessment

The appropriateness of the structural model was evaluated against four criteria—multicollinearity, explanatory power, effect sizes, and model fit—prior to hypothesis testing.

Multicollinearity was assessed using inner VIF values for each predictor of endogenous constructs. Both AI literacy (VIF = 1.301) and coaching leadership (VIF = 1.226) fell below the conservative threshold of 3.0, confirming the absence of collinearity concerns.

Explanatory power indicated by R^2 was .485 for innovative behavior and .157 for AI literacy. The R^2 of .485 for innovative behavior indicates that coaching leadership and AI literacy together explained approximately 49% of the variance in innovative behavior, approaching the moderate level by Hair et al.'s (2019) criteria. The R^2 of .157 for AI literacy was relatively modest; however, given that coaching leadership was the sole substantive predictor of AI literacy in the model, and that AI literacy is likely influenced by numerous other factors (e.g., technology affinity, prior IT experience, organizational digital environment), the finding that coaching leadership alone explained 15.7% of the variance is interpreted as practically meaningful.

Effect sizes (f^2) were evaluated against Cohen's (1988) benchmarks (.02 = small, .15 = medium, .35 = large). The AI literacy → innovative behavior path yielded $f^2 = .543$ (large effect), and the coaching leadership → AI literacy path yielded $f^2 = .187$ (medium effect), confirming that both core paths possessed substantive effect sizes.

Predictive relevance was assessed using Stone-Geisser's Q^2 values obtained through a blindfolding procedure (omission distance = 7). The Q^2 value for innovative behavior was .448, indicating medium-to-large predictive relevance, and the Q^2 value for AI literacy was .164, indicating small-to-medium predictive relevance (Hair et al., 2019). Both values exceeded zero, confirming that the structural model possesses adequate out-of-sample predictive power. The relatively modest Q^2 for AI literacy is consistent with the model specification in which coaching leadership serves as the sole substantive predictor; AI literacy is likely influenced by additional factors not included in the present model.

Model fit was assessed through SRMR, which was .023 (saturated model), substantially below Hu and Bentler's (1999) criterion of .08, indicating excellent model fit.

In summary, the structural model met or exceeded all recommended criteria (Hair et al., 2019) for R^2, f^2, VIF, Q^2, and SRMR, thereby establishing the reliability of subsequent hypothesis testing results.

4.6. Hypothesis Testing

Structural model testing was conducted using bootstrapping (5,000 replications) in SmartPLS 4.0. The unidimensional model was used to test primary research hypotheses (H1–H6) and exploratory research questions (RQ2, RQ3), while the sub-dimension model was used for the exploratory research question RQ1. Gender, age, education level, and job rank were entered as control variables for the dependent variable (innovative behavior), but none reached significance (gender: $\beta = .005$, $p = .946$; age: $\beta = .035$, $p = .370$; education: $\beta = -.009$, $p = .803$; job rank: $\beta = -.012$, $p = .729$). This indicates that the effects identified in this study are robust and not attributable to demographic characteristics.

4.6.1. Direct Effects (H1–H3)

For Hypothesis 1, supervisors' coaching leadership showed a statistically significant but practically modest positive association with innovative behavior after controlling for AI literacy ($\beta = .096$, SE = .100, $t = 1.983$, $p = .047$); thus, Hypothesis 1 was supported in the sense that the direct association remained distinguishable from zero. However, several caveats are warranted. First, $\beta = .096$ constitutes a small effect by Cohen's (1988) standards and falls at the boundary of conventional significance ($p = .047$), indicating limited evidential weight for a strong direct effect of coaching leadership on innovative behavior. Second, this direct effect is estimated after partialling out the substantial indirect pathway through AI literacy ($\beta = .258$); when the indirect pathway is considered, the total effect of coaching leadership on innovative behavior is $\beta = .354$, of which only 27.1% constitutes the direct component. Therefore, this finding is most appropriately interpreted not as evidence that coaching leadership directly stimulates innovative behavior, but rather as confirmation that a residual direct association exists alongside the dominant indirect pathway through AI competency development. The substantive story of coaching leadership's role in fostering innovative behavior is more accurately told through the mediation analysis presented in Section 4.6.3.

For Hypothesis 2, supervisors' coaching leadership exhibited a significant positive effect on AI literacy ($\beta = .397$, SE = .038, $t = 10.458$, $p < .001$). The β of .397 represented a medium effect size ($f^2 = .187$), demonstrating that supervisors' coaching leadership exerts a substantive influence on employees' AI competency development. Given that only 21.9% of the sampled firms possessed formal AI training programs, coaching leadership may function as a critical learning pathway that supplements or substitutes for formal training in SMEs.

For Hypothesis 3, AI literacy exhibited a significant positive effect on innovative behavior ($\beta = .649$, SE = .029, $t = 22.038$, $p < .001$). The β of .649 represented a large effect size ($f^2 = .543$) and was confirmed as the strongest path in the research model. This finding empirically demonstrates that the integrated competency of understanding AI, critically evaluating it, and applying it ethically and creatively serves as a core driver of innovative behavior.

Regarding the main effects of the moderators, instrumental support exhibited a significant positive effect on innovative behavior ($\beta = .258$, $t = 2.527$, $p = .011$), whereas psychological support did not significantly predict innovative behavior ($\beta = -.059$, $p = .564$).

4.6.2. Exploratory Sub-Dimension Analysis (Research Question 1)

To examine the differential effects of the four coaching leadership sub-dimensions on AI literacy, a sub-dimension level path model was estimated. As shown in Table 2, under conditions of severe multicollinearity (VIF = 10.9–13.1 across coaching leadership sub-dimensions), relationship building was the only sub-dimension whose regression coefficients retained significance across all four AI literacy sub-dimensions: AI utilization ability ($\beta = .373$, $t = 2.573$, $p = .010$), critical evaluation ($\beta = .302$, $t = 2.144$, $p = .032$), ethical use ($\beta = .287$, $t = 2.032$, $p = .042$), and creative application ($\beta = .376$, $t = 2.628$, $p = .009$). Direction setting ($\beta = .020$–$.070$, $p > .05$), performance evaluation ($\beta = -.125$ to $-.017$, $p > .05$), and competency development ($\beta = .053$–$.120$, $p > .05$) did not yield significant coefficients for any AI literacy sub-dimension in the simultaneous model.

It must be emphasized that this pattern of results is subject to substantial interpretation constraints. When predictors are correlated at $r = .929$–$.940$ and VIF values exceed 10, the allocation of shared variance among predictors in simultaneous regression is inherently unstable; the exclusive significance of relationship building may reflect which predictor happens to capture the shared variance under a particular collinearity structure rather than a genuine differential theoretical mechanism. The finding that relationship building was statistically distinguishable from zero while the other three sub-dimensions were not should therefore not be read as evidence that "relationship building is the key dimension of coaching leadership for AI literacy development." The more defensible interpretation is that, within the constraints of the present simultaneous estimation, relationship building showed the most stable pattern of associations with AI literacy sub-dimensions. This pattern awaits replication under conditions of greater dimensional separation—either through instruments specifically designed to minimize inter-subscale correlations, or through analytic strategies such as dominance analysis or relative weight analysis that are better suited to highly correlated predictor sets.

Table 4: Coaching Leadership Sub-Dimensions Predicting AI Literacy Sub-Dimensions

CL Sub-Dimension	AIL Sub-Dimension	β	t	p
Direction Setting	AI Utilization Ability	.044	0.289	.773
	Critical Evaluation	.070	0.477	.634
	Ethical Use	.020	0.128	.898
	Creative Application	.037	0.248	.804
Performance Evaluation	AI Utilization Ability	−.125	0.846	.397
	Critical Evaluation	−.017	0.113	.910
	Ethical Use	−.036	0.231	.818
	Creative Application	−.077	0.521	.602
Competency Development	AI Utilization Ability	.085	0.610	.542
	Critical Evaluation	.053	0.396	.692
	Ethical Use	.120	0.893	.372
	Creative Application	.069	0.520	.603
Relationship Building	AI Utilization Ability	.373	2.573	.010
	Critical Evaluation	.302	2.144	.032
	Ethical Use	.287	2.032	.042
	Creative Application	.376	2.628	.009

Robustness checks for sub-dimension analysis. Given the extremely high inter-correlations among coaching leadership sub-dimensions (bivariate r = .929–.940; VIF = 10.9–13.1 in simultaneous estimation), supplementary analyses were conducted to assess the stability of the differential pattern. Three complementary approaches were employed.

First, at the bivariate level, relationship building exhibited the largest zero-order correlations with AI literacy and all its sub-dimensions (r = .375–.402), compared with direction setting (r = .360–.385), performance evaluation (r = .343–.377), and competency development (r = .362–.385). Although the differences were modest in absolute magnitude (.02–.03), relationship building consistently ranked highest across all eight correlation pairs.

Second, Lindeman-Merenda-Gold (LMG) relative importance analysis (Grömping, 2006) was conducted for the prediction of composite AI literacy. Relationship building accounted for 31.2% of the explained variance, compared with competency development (23.7%), direction setting (23.1%), and performance evaluation (22.1%). This analysis decomposes R^2 in a manner that is less sensitive to collinearity than standardized regression coefficients.

Third, bootstrapped OLS regression (5,000 replications) was conducted for each of the 16 paths (4 CL sub-dimensions × 4 AIL sub-dimensions). Relationship building was the only sub-dimension for which the 95% bootstrap confidence interval excluded zero across all four AI literacy sub-dimensions (proportion of positive bootstrap estimates: 98.0–99.6%). For the other three sub-dimensions, confidence intervals included zero in all cases (proportion of positive estimates: 17.7–81.7%).

Taken together, these supplementary analyses reveal a directionally consistent but statistically fragile pattern: relationship building demonstrated marginally higher bivariate correlations (r = .375–.402 vs. .343–.385 for other sub-dimensions; difference = .02–.03), the highest LMG relative importance weight (31.2% vs. 22.1–23.7%), and was the only sub-dimension whose bootstrap confidence intervals consistently excluded zero across all 16 paths. While this convergent multi-method pattern provides some directional support for the differential role of relationship building, the effect size differences are modest and the estimation instability induced by VIF values exceeding 10 means that these results carry limited inferential weight. Therefore, this pattern of findings should be treated strictly as a hypothesis-generating observation: it raises the possibility that relationship building may function as a differentially important mechanism for AI literacy development, particularly in contexts of intergenerational competence reversal, but this possibility requires confirmation through studies employing instruments with greater dimensional separation and samples in which coaching leadership sub-dimensions exhibit more discriminant variance.

These differential results may be interpreted in relation to the phenomenon of intergenerational competence reversal in the AI domain. Given that 89.3% of supervisors in the present sample were aged 40 or older, it is difficult to assume that supervisors invariably possess superior AI utilization competencies relative to their subordinates. In this context, leadership behaviors such as direction setting, competency development, and performance evaluation, which are grounded in the supervisor's technical knowledge or evaluative authority, may lack sufficient content credibility in the AI domain. By contrast, relationship building is a leadership behavior that can be exercised regardless of the supervisor's AI competency level; its essence lies in creating an environment where employees can attempt new approaches without fear of failure through trust formation and psychological safety provision.

The individual effects of the four AI literacy sub-dimensions on innovative behavior were all nonsignificant (AI utilization ability: $\beta = .202$, $p = .107$; critical evaluation: $\beta = .179$, $p = .087$; ethical use: $\beta = .157$, $p = .530$; creative application: $\beta = .133$, $p = .233$). This pattern is interpreted as reflecting multicollinearity due to high inter-correlations among sub-dimensions (HTMT: .834–.842). Considering that AI literacy as a unidimensional construct exhibited a strong effect ($\beta = .649$), the results suggest that the four sub-dimensions contribute to innovative behavior as an integrated competency through complementary combination rather than independent operation.

4.6.3. Mediation Analysis (H4)

Using bias-corrected 95% confidence intervals (Bca CI; Hayes, 2018), the indirect effect of coaching leadership on innovative behavior through AI literacy was significant ($\beta = .258$, $SE = .029$, $t = 8.869$, $p < .001$), with the 95% CI [.201, .314] not containing zero. Because the direct effect ($\beta = .096$, $p = .047$) also remained significant, partial mediation was confirmed.

The finding that the indirect effect ($\beta = .258$) was approximately 2.7 times larger than the direct effect ($\beta = .096$) indicates that a substantial portion of coaching leadership's influence on innovative behavior is transmitted through the competency-based mechanism of AI literacy. The proportion of the indirect effect relative to the total effect (indirect/total = .258/.354 = 72.9%) demonstrates that AI literacy serves as the primary mechanism through which the effects of coaching leadership are conveyed to innovative behavior. Hypothesis 4 was supported.

4.6.4. Moderation Analysis (H5–H6)

Primary analysis — Unified AI-POS moderator (Hypothesis 5). Consistent with the measurement model finding that instrumental and psychological support are empirically non-separable in the present sample, the primary moderation analysis employed the unified AI-POS composite as the moderator. The AI literacy × AI-POS interaction was significantly and positively associated with innovative behavior ($\beta = .181$, $SE = .036$, $t = 4.963$, $p < .001$, 95% Bca CI [.109, .244]), supporting Hypothesis 5. This finding confirms that organizational AI support as a whole strengthens the positive association between AI literacy and innovative behavior, consistent with the AMO framework's proposition that Opportunity factors are necessary for Ability to translate into Performance.

However, given the empirical non-separability of the two AI-POS dimensions documented in Section 4.3 (CFA inter-factor correlation = 1.000), the differential significance of H5 versus H6 may reflect collinearity-induced suppression rather than a genuine theoretical distinction. To assess the robustness of the moderation findings, three supplementary models were estimated: These supplementary analyses were conducted using OLS regression with standardized variables and bias-corrected and accelerated (Bca) bootstrap confidence intervals based on 5,000 replications. This approach provides results that are directly comparable to PLS-SEM path coefficients while allowing each moderator to be examined free from mutual collinearity. (a) a model with instrumental support as the sole moderator (excluding psychological support), (b) a model with psychological support as the sole moderator (excluding instrumental support), and (c) a model with a unidimensional AI-POS composite (averaging all six items) as the moderator. As shown in Table 5, all three specifications yielded significant positive moderation of the AI literacy–innovative behavior relationship: instrumental support alone ($\beta = .187$, $SE = .036$, $t = 5.159$, $p < .001$, 95% Bca CI [.116, .250]), psychological support alone ($\beta = .165$, $SE = .037$, $t = 4.497$, $p < .001$, 95% Bca CI [.094, .232]), and unified AI-POS ($\beta = .181$, $SE = .036$, $t = 4.963$, $p < .001$, 95% Bca CI [.109,

.244]). These results confirm that organizational AI support strengthens the conversion of AI literacy into innovative behavior, but do not support a confident conclusion regarding the differential importance of instrumental versus psychological support.

Table 5: Supplementary Moderation Analyses: Alternative Model Specifications

Model Specification	Moderator	β	SE	t	p	95% Bca CI
Original (simultaneous)	Instrumental Support	.248	.094	2.633	.009	—
Original (simultaneous)	Psychological Support	−.065	.094	−0.696	.487	—
Separate model (a)	Instrumental Support only	.187	.036	5.159	< .001	[.116, .250]
Separate model (b)	Psychological Support only	.165	.037	4.497	< .001	[.094, .232]
Separate model ©	Unified AI-POS	.181	.036	4.963	< .001	[.109, .244]

Note. Interaction effect of AI literacy × moderator on innovative behavior. Original model enters both moderators and both interaction terms simultaneously. Separate models enter one moderator and its interaction term only. Unified AI-POS averages all six AI-POS items into a single composite. OLS regression with standardized variables; bootstrap 95% Bca confidence intervals based on 5,000 replications. Control variables (gender, age, education, job rank) included in all models.

Exploratory supplementary analysis — Dimension-level moderation (Research Question 2). To address Research Question 2, three supplementary specifications were estimated: (a) instrumental support as the sole moderator, (b) psychological support as the sole moderator, and (c) simultaneous entry of both dimensions. In the simultaneous model, the interaction between AI literacy and instrumental support was significant (β = .223, SE = .101, t = 2.201, p = .028), while the interaction with psychological support was nonsignificant (β = −.046, SE = .103, t = 0.444, p = .657). However, as anticipated given the near-perfect inter-correlation between the two dimensions (r = .928), the simultaneous model results are likely affected by collinearity-induced suppression. When each dimension was tested in isolation, both instrumental support (β = .187, SE = .036, t = 5.159, p < .001, 95% Bca CI [.116, .250]) and psychological support (β = .165, SE = .037, t = 4.497, p < .001, 95% Bca CI [.094, .232]) functioned as significant positive moderators. Therefore, with respect to Research Question 2, the present data do not provide a basis for confidently concluding that instrumental support is inherently more important than psychological support; both dimensions appear capable of moderating the AI literacy–innovative behavior relationship, and the differential significance in the simultaneous model is more plausibly attributed to measurement-level collinearity than to a genuine theoretical distinction.

4.6.5. Moderated Mediation Analysis (H6 and RQ3)

Hypothesis 6 and Research Question 3 examined whether the indirect effect (coaching leadership → AI literacy → innovative behavior) varied as a function of organizational support level. The moderator was divided into three levels (mean ± 1 SD), conditional indirect effects were computed for each level, and overall significance was evaluated using the index of moderated mediation (Hayes, 2018). Results are presented in Table 5.

Table 6: Moderated Mediation Analysis: Conditional Indirect Effects by AI-POS Level

Moderator	Level	Conditional Indirect Effect	95% CI	*p*
Instrumental Support	Low (−1 *SD*)	.167	[.079, .264]	< .001
	Mean	.256	[.200, .313]	< .001
	High (+1 *SD*)	.344	[.247, .454]	< .001
	Index of Moderated Mediation	.089	—	< .05
Psychological Support	Low (−1 *SD*)	.274	[.183, .377]	< .001

	Mean	.256	[.200, .313]	< .001
	High (+1 *SD*)	.238	[.144, .340]	< .001
	Index of Moderated Mediation	−.018	—	*n.s.*

Note. Conditional indirect effects represent the effect of coaching leadership on innovative behavior through AI literacy at different levels of AI-POS. Bootstrap 95% Cis based on 5,000 replications. Index of moderated mediation: instrumental support = .397 × .223 = .089; psychological support = .397 × (−.046) = −.018.

For instrumental support, the conditional indirect effects progressively increased from .167 at low levels (−1 SD) to .344 at high levels (+1 SD), representing an approximately 2.1-fold amplification. The index of moderated mediation was .089 ($p < .05$); thus, Hypothesis 6 was supported. This indicates that when tangible organizational resource support is sufficient, the indirect effect of coaching leadership on innovative behavior through AI literacy is amplified approximately 2.1-fold.

In contrast, conditional indirect effects by psychological support level were β = .274 at low, β = .256 at mean, and β = .238 at high, all significant at each level; however, differences across levels were limited and exhibited a weak reverse-direction pattern. The index of moderated mediation was −.018, which was nonsignificant; the moderated mediation index for Research Question 3b was nonsignificant.

4.7. Summary of Hypothesis Testing

Table 7 presents a comprehensive summary of all hypothesis testing results.

Table 6: Moderated Mediation Analysis: Conditional Indirect Effects by AI-POS Level

Hypothesis / RQ	Path	β	t	p	95% BCa CI	f^2	Result
H1	CL → IB (direct)	.096	1.983	.047	—	.012	Supported†
H2	CL → AIL	.397	10.458	< .001	—	.187	Supported
H3	AIL → IB	.649	22.038	< .001	—	.543	Supported
H4	CL → AIL → IB (mediation)	.258	8.869	< .001	[.201, .314]	—	Supported
H5 (Primary)	AIL × AI-POS (unified) → IB	.181	4.963	< .001	[.109, .244]	—	Supported
RQ2-a (Exploratory)	AIL × IS → IB (IS sole moderator)	.187	5.159	< .001	[.116, .250]	—	Significant
RQ2-b (Exploratory)	AIL × PS → IB (PS sole moderator)	.165	4.497	< .001	[.094, .232]	—	Significant
RQ2-sim (Reference)	AIL × IS → IB (simultaneous)	.223	2.201	.028	[.034, .432]	—	Significant
RQ2-sim (Reference)	AIL × PS → IB (simultaneous)	−.046	0.444	.657	[−.259, .148]	—	n.s. (collinearity)
H6 (Primary)	Moderated Mediation (unified AI-POS)	Index = .072	—	< .05	—	—	Supported
RQ3-a (Exploratory)	Moderated Mediation (IS only)	Index = .089	—	< .05	—	—	Significant
RQ3-b (Exploratory)	Moderated Mediation (PS only)	Index = −.018	—	n.s.	—	—	n.s.

Note. H1–H4 and H5–H6 represent primary hypotheses; RQ2 and RQ3 represent exploratory research questions. The moderated mediation index for H6 (Index = .072) was computed using the unified AI-POS composite score (average of all six AI-POS items) as the moderator in a bootstrapping procedure (5,000 replications). RQ2 and RQ3 results are reported as supplementary exploratory findings and do not constitute the basis for hypothesis acceptance or rejection. CL = Coaching Leadership; AIL = AI Literacy; IS = Instrumental Support; PS = Psychological Support; IB = Innovative Behavior; AI-POS = AI-Contextualized Perceived Organizational Support. Bootstrap 95% BCa confidence intervals based on 5,000 replications. Control variables (gender, age, education, job rank) were included in all models but were nonsignificant. Effect size benchmarks: f^2 = .02 (small), .15 (medium), .35 (large; Cohen, 1988).

Of the six primary hypotheses (H1–H6), all were supported. H1 was supported in the sense that the direct association of coaching leadership with innovative behavior remained statistically distinguishable from zero (β = .096, p = .047), though the effect was modest and should be interpreted primarily in the context of the dominant indirect pathway confirmed by H4. H2, H3, H4, H5, and H6 were all supported with medium-to-large effect sizes. Supplementary exploratory analyses for RQ2 indicated that both instrumental and psychological support individually moderated the AI literacy–innovative behavior relationship when tested as sole moderators, though the two dimensions could not be distinguished in simultaneous estimation due to near-perfect empirical overlap. The exploratory research question RQ1 revealed a directionally consistent but multicollinearity-constrained pattern in which relationship building showed the most stable associations with all AI literacy sub-dimensions (β = .287–.376 in the simultaneous model); however, this finding is treated as hypothesis-generating given VIF values exceeding 10 among coaching leadership sub-dimensions.

5. Discussion

5.1. Summary of Findings

This study examined the association between supervisors' coaching leadership and innovative behavior through the mediating pathway of AI literacy and the moderating effect of AI-POS using PLS-SEM with a sample of 429 SME employees. All six primary hypotheses (H1–H6) were supported, and supplementary exploratory analyses for RQ1, RQ2, and RQ3 yielded meaningful patterns warranting future investigation.

Regarding direct effects, coaching leadership was strongly and positively associated with AI literacy (β = .397, p < .001) and exhibited a modest but statistically significant residual association with innovative behavior after accounting for AI literacy (β = .096, p = .047). AI literacy itself exhibited the strongest association with innovative behavior in the research model (β = .649, p < .001). The mediation analysis revealed that AI literacy significantly mediated the coaching leadership–innovative behavior relationship (indirect effect β = .258, 95% CI [.201, .314]), with the indirect effect accounting for approximately 72.9% of the total effect. This pattern indicates that coaching leadership operates primarily as an enabler of employees' AI competency development, and it is through this competency development pathway—rather than through direct supervisory influence—that coaching leadership is most consequentially linked to innovative behavior.

Regarding moderation, the primary analysis using the unified AI-POS composite confirmed that organizational AI support as a whole significantly moderates the AI literacy–innovative behavior relationship (β = .181, p < .001), supporting the AMO framework's proposition that Opportunity factors are necessary for Ability to translate into Performance. Supplementary dimension-level analyses indicated that both instrumental support (β = .187, p < .001) and psychological support (β = .165, p < .001) independently moderated the relationship when each was tested in isolation; however, the near-perfect empirical overlap between the two dimensions (inter-factor correlation = 1.000 in CFA) prevents confident conclusions regarding their differential importance.

Moderated mediation testing confirmed that the primary moderated mediation index using the unified AI-POS composite was significant (Index = .072, p < .05; H6 supported). Supplementary exploratory analyses further indicated that the indirect effect progressively strengthened as instrumental support increased (.167 → .256 → .344; RQ3-a significant), while the moderated mediation index for psychological support was nonsignificant (Index = −.018; RQ3-b nonsignificant). The exploratory sub-dimension analysis revealed that only the relationship-building dimension among the four coaching leadership sub-dimensions exhibited significant positive effects on all AI literacy sub-dimensions (β = .287–.376), while direction setting, performance evaluation, and competency development were all nonsignificant.

5.2. Discussion of Key Findings

Three core findings from the present study merit particular attention.

First, the finding that the indirect effect (β = .258) was approximately 2.7 times larger than the direct effect (β = .096) suggests that the association between coaching leadership and innovative behavior is primarily channeled through the competency-based mechanism of AI literacy. This constitutes an empirical validation, within the AI context, of the triadic reciprocal causation model of social cognitive theory—the environment (coaching leadership) → cognition (AI literacy) → behavior (innovative behavior) pathway (Bandura, 1986)—and the potential-to-realized absorptive capacity conversion mechanism posited by absorptive capacity theory (Zahra & George, 2002). Given that only 21.9% of firms in the sample possessed formal AI training programs, coaching leadership may serve as a learning pathway that supplements formal training in SMEs.

Second, the sub-dimension analysis revealed a directionally consistent but statistically fragile pattern in which relationship building showed the most stable associations with AI literacy across multiple analytic approaches. However, the framing of this finding requires careful calibration. Given the extreme inter-correlations among coaching leadership sub-dimensions ($r = .929–.940$) and VIF values exceeding 10 in the simultaneous model, the appropriate conclusion is not that "relationship building is the key dimension of coaching leadership for AI literacy development" but rather that "across the analytic methods employed in this study—bivariate correlations, LMG relative importance analysis, and bootstrapped OLS regression—relationship building showed a marginally and directionally more stable pattern of association with AI literacy than the other three sub-dimensions, but this advantage was modest in magnitude (.02–.03 in bivariate r) and subject to substantial estimation uncertainty." This finding is best treated as a hypothesis that warrants confirmation in future studies employing instruments with greater dimensional separation or analytic strategies specifically designed for highly correlated predictor sets. Three theoretical considerations may help explain why relationship building showed relatively greater stability. First, regarding intergenerational competence reversal, given that 89.3% of supervisors in the present sample were aged 40 or older, direction setting, competency development, and performance evaluation—behaviors grounded in expert power (French & Raven, 1959)—may lack sufficient content credibility in a domain where supervisors may not possess superior AI competency. Relationship building, operating through referent power, is exercisable regardless of the supervisor's technical proficiency. Second, from the self-determination theory perspective (Ryan & Deci, 2000), relationship building may uniquely satisfy the need for relatedness and create psychological safety (Edmondson, 1999) that facilitates voluntary AI exploration, whereas directive or evaluative behaviors may constrain autonomy or undermine safety. Third, the K-SCLS development study (Lee, 2025) confirmed a balanced bifactor structure (ECVH = 58.2%), indicating that specific variance exists beyond the general factor, though the amount is limited.

However, critical caveats must accompany this interpretation. The bivariate correlation differences are modest (.02–.03), and VIF values exceeding 10 indicate that the simultaneous regression coefficients are subject to substantial estimation instability. The exclusive significance of relationship building in the PLS-SEM sub-dimension model may partly reflect which predictor happens to capture the shared variance first under severe multicollinearity rather than a genuine differential mechanism. That said, the theoretical reasoning offered for why relationship building might function as the more important dimension in contexts of intergenerational competence reversal—where supervisors cannot rely on expert power in the AI domain and must instead leverage referent power through trust and psychological safety—remains theoretically coherent and empirically consistent with the broader pattern of results. This theoretical logic provides a useful foundation for future hypothesis-driven research, even as the present findings cannot confirm it conclusively.

Third, the original analysis appeared to show differential moderation by instrumental versus psychological support; however, supplementary analyses revealed that this pattern is more parsimoniously explained by collinearity between the two empirically non-separable dimensions rather than by a genuine theoretical distinction. When each dimension was tested in a separate model free from mutual suppression, both instrumental support ($\beta = .187$, $p < .001$) and psychological support ($\beta = .165$, $p < .001$) significantly moderated the AI literacy–innovative behavior relationship, and a unidimensional AI-POS composite also showed significant moderation ($\beta = .181$, $p < .001$). Therefore, the present data support the conclusion that organizational AI support as a whole strengthens the conversion of AI literacy into innovative behavior, consistent with the AMO framework's proposition that Opportunity factors are necessary for Ability to translate into performance. The question of whether instrumental and psychological support operate through distinct mechanisms in the AI context remains open and warrants investigation with more refined measurement instruments. From the AMO model perspective, the key practical implication remains intact: for AI literacy (Ability) to be converted into innovative behavior (Performance), organizational support that provides Opportunity for its exercise is essential.

5.3. Theoretical Implications

The theoretical contributions and their boundaries are discussed in four points, with each contribution accompanied by an explicit acknowledgment of the limitations that constrain its interpretive scope.

First, this study provides exploratory empirical evidence for a pathway connecting coaching leadership and AI literacy, extending prior research that remained at the digital literacy level (Kim & Oh, 2023) or focused on traditional leadership outcome variables. The finding that the indirect pathway through AI literacy ($\beta = .258$) was approximately 2.7 times larger than the direct association ($\beta = .096$) is consistent with social cognitive theory's triadic reciprocal causation model and absorptive capacity theory's potential-to-realized conversion mechanism (Zahra & George, 2002). However, the cross-sectional design precludes confirmation of causal directionality; the observed pattern is equally consistent with reverse causation (e.g., innovative employees perceiving their supervisors' coaching more favorably) or reciprocal causation. Additionally, AI literacy was measured through self-report rather than performance-based assessment, which may have inflated the strength of the mediation pathway due to shared method variance. Therefore, while the present findings suggest a promising theoretical direction, the causal pathway remains to be confirmed through longitudinal or experimental designs.

Second, the finding that only the relationship-building dimension exhibited significant associations with all AI literacy sub-dimensions offers an intriguing exploratory insight regarding the role of referent-power-based relational leadership in domains characterized by intergenerational competence reversal. This finding is directionally supported by multiple robustness checks: relationship building demonstrated the largest bivariate correlations with AI literacy (r = .402 vs. .376–.384), the highest relative importance weight (LMG = 31.2% vs. 22.1–23.7%), and was the only sub-dimension whose bootstrap confidence intervals consistently excluded zero across all 16 paths. Nevertheless, the extreme inter-correlations among coaching leadership sub-dimensions (r = .929–.940, VIF > 10) severely limit the stability of individual regression coefficients in simultaneous estimation. Consequently, this finding should be treated as hypothesis-generating rather than confirmatory, awaiting replication with instruments that achieve greater dimensional separation or with analytic approaches (e.g., dominance analysis, relative weight analysis, or latent profile analysis) better suited to highly correlated predictors.

Third, the introduction of AI-contextualized perceived organizational support (AI-POS) represents an initial attempt to extend the AMO framework to the AI technology domain. The original analysis suggested differential moderation by instrumental versus psychological support; however, supplementary analyses revealed that the two dimensions were empirically non-separable in the present data (CFA inter-factor correlation = 1.000; $\Delta\chi^2 = 0.27$, p = .603 for the single- vs. two-factor comparison). When each dimension was tested in separate models, both instrumental support (β = .187, $p < .001$) and psychological support (β = .165, $p < .001$) significantly moderated the AI literacy–innovative behavior relationship, and a unidimensional AI-POS composite also showed significant moderation (β = .181, $p < .001$). Therefore, the more defensible conclusion from the present data is that organizational support for AI utilization as a whole strengthens the conversion of AI literacy into innovative behavior, rather than that instrumental support is inherently more important than psychological support. The theoretical question of whether these two dimensions are genuinely separable in the AI context requires further investigation with expanded item pools and independent-sample validation.

Fourth, by examining these mechanisms within the resource-constrained SME context—where only 21.9% of firms possessed formal AI training programs—this study complements the existing literature that has predominantly focused on large corporations. The use of culturally validated Korean instruments (K-SCLS and the Korean Generative AI Literacy Scale) strengthens the cultural validity of the findings. However, the nonprobability sample screened for AI tool experience or intention limits generalizability to SME employees broadly; the findings are most directly applicable to employees who have already engaged with or are receptive to AI technology.

5.4. Practical Implications

The practical implications of this study are as follows.

First, SME leadership development programs should recognize that coaching leadership's primary contribution to employee innovation lies in its capacity to develop employees' AI literacy rather than in directly stimulating innovative behavior. Given that approximately 72.9% of the total effect of coaching leadership on innovative behavior was transmitted through AI literacy in the present study, leadership development initiatives should be explicitly positioned as AI competency enablement programs. This reframing has practical consequences: the success of coaching leadership development should be evaluated not only in terms of whether innovative behavior increases, but more proximally in terms of whether employees' AI literacy—their capacity to utilize, critically evaluate, ethically apply, and creatively leverage AI—improves as a result.

Within this context, the exploratory sub-dimension analysis offered a tentative suggestion that relationship-building behaviors may be particularly relevant for AI literacy development in contexts where supervisors do not possess superior AI expertise relative to their subordinates (intergenerational competence reversal). Building trust, demonstrating openness to subordinates' ideas, and cultivating psychological safety may enable employees to experiment with AI without fear of negative evaluation. However, given the multicollinearity constraints documented in this study (r = .929–.940 among sub-dimensions, VIF > 10), this suggestion should be treated as a hypothesis for further investigation rather than a confirmed basis for reallocating training resources toward relationship building specifically. The more conservative practical recommendation is to develop coaching leadership competencies holistically, with particular attention to the relational dimensions of coaching, pending replication of the sub-dimension pattern in studies with more dimensionally separable instruments.

Second, in designing AI support systems, organizations should recognize that organizational AI support as a whole—encompassing both tangible resources (AI tool licenses, training opportunities, time and budget allocations) and psychological support (tolerance for failure, encouragement of experimentation)—functions as a significant opportunity factor that amplifies the conversion of employees' AI literacy into innovative behavior. The present study could not reliably distinguish the relative importance of instrumental versus psychological support due to the near-perfect empirical overlap between the two dimensions; both dimensions independently demonstrated significant moderating effects when examined in isolation. Therefore, rather than prioritizing one form of support over the other based on the present findings, the most evidence-consistent recommendation is a comprehensive support approach: organizations should invest simultaneously in tangible AI infrastructure and in a psychologically safe organizational climate. Given the resource constraints typical of SMEs, a phased implementation strategy may be practical—prioritizing immediate access to AI tools (instrumental support) in the first phase while deliberately building a culture of experimentation and tolerance for failure (psychological support) as a concurrent, longer-term initiative.

Third, AI literacy education should be designed to comprehensively and equitably encompass the four dimensions of AI utilization ability, critical evaluation, ethical use, and creative application, rather than being limited to tool usage methods. Given the powerful effect of AI literacy on innovative behavior (β = .649), multidimensional AI competency development represents a core strategy for innovation promotion.

Fourth, coaching leadership development and AI support infrastructure should be designed and implemented as an integrated—rather than separate—initiative. As confirmed through the moderated mediation analysis, the indirect effect on innovative behavior is amplified approximately 2.1-fold (.167 → .344) when AI literacy is developed through coaching leadership and instrumental support is provided simultaneously.

Fifth, considering intergenerational AI competence reversal, organizations should cultivate peer-based informal learning networks, reverse mentoring programs, and team-level AI learning cultures rather than relying solely on supervisors' technical coaching. This represents a complementary practical approach to the finding that supervisors' relationship building contributes most effectively to AI literacy.

5.5. Limitations and Future Research Directions

This study possesses the following limitations. First, the cross-sectional design constitutes the most fundamental limitation of the present study, precluding any definitive conclusions regarding the directionality of the observed relationships. Three specific alternative causal interpretations remain plausible and cannot be distinguished from the theorized direction using the present data. (a) Reverse causation: employees who already demonstrate innovative behavior may elicit more coaching from their supervisors through a followership effect, or employees with high AI literacy may perceive the same supervisory behaviors more favorably due to a cognitive framing effect. (b) Reciprocal causation: consistent with social cognitive theory's triadic reciprocal causation model, which inherently presupposes bidirectional influence among personal, behavioral, and environmental factors (Bandura, 1986), the relationships among coaching leadership, AI literacy, and innovative behavior may be mutually reinforcing rather than unidirectional. (c) Third-variable explanation: unmeasured individual differences such as general cognitive ability, openness to experience, or proactive personality may simultaneously predict favorable perceptions of coaching leadership, higher AI literacy, and greater innovative behavior, creating spurious associations among the study variables. Accordingly, the path coefficients reported in this study should be interpreted as reflecting the strength and direction of associations that are consistent with—but do not confirm—the theorized causal sequence. Future research should employ at minimum three-wave longitudinal panel designs with cross-lagged specifications, or quasi-experimental interventions (e.g., coaching leadership training programs with pre-post AI literacy and innovative behavior measurement), to establish temporal precedence and strengthen causal inference.

Second, because all variables were measured through self-report from the same respondents at a single time point, common method bias remains a concern that cannot be fully resolved through statistical diagnostics alone. Although multiple post hoc tests (full collinearity VIF, Harman's CFA test, ULMC analysis, and differential correlation patterns) collectively suggested that CMB did not fundamentally alter the core findings, these diagnostics provide only indirect and partial evidence. The fact that coaching leadership perceptions, AI literacy self-assessments, and innovative behavior self-reports are all susceptible to social desirability bias means that the observed path coefficients may reflect some degree of shared method variance that statistical corrections cannot entirely eliminate. Future research should address this limitation through three specific design improvements: (a) measuring innovative behavior through supervisor ratings, peer evaluations, or objective indicators (e.g., patent applications, implemented process improvements) to establish a multi-source measurement framework; (b) employing longitudinal designs with temporal separation between predictor, mediator, and outcome measurement occasions (e.g., coaching leadership at T1, AI literacy at T2, innovative behavior at T3) to reduce consistency motives; and (c) supplementing self-reported AI literacy with performance-based assessments (e.g., task-based AI utilization tests) to triangulate competency measurement.

Third, the AI-POS scale is an early-stage instrument newly conceptualized in this study, and its current form carries structural limitations that substantially constrained the interpretive scope of the moderation findings. The near-perfect empirical overlap between the instrumental and psychological support dimensions (r = .928; CFA inter-factor correlation = 1.000) rendered them inseparable in the present data, meaning that the theoretically motivated two-dimension distinction could not be empirically tested in the intended manner. This limitation likely stems from at least three interrelated sources. First, the subscales contain only three items each—a minimum that provides little within-dimension variance for capturing the conceptual distinctions between resource provision and emotional support. Research on scale development consistently demonstrates that subscales with three or fewer items are particularly vulnerable to empirical collapse when the underlying constructs are conceptually adjacent (Clark & Watson, 1995). Second, the items were adapted from a general perceived organizational support framework (Eisenberger et al., 1986) rather than developed de novo from an AI-specific conceptual model; it is possible that the adapted items did not successfully instantiate the intended conceptual distinctions in the Korean SME context. Third, because AI tool adoption in SMEs is still at an early stage (only 21.9% of firms in the sample had formal AI training programs), employees may not yet have developed sufficiently differentiated perceptions of the two support types—perceiving organizational AI support in holistic rather than faceted terms.

Future scale development for AI-POS should address these limitations through a systematic process: (a) beginning with an expanded item pool of at least five items per dimension, grounded in a conceptual analysis of what distinguishes resource-based support from emotional-climatic support specifically in the AI technology domain; (b) conducting expert panel review and cognitive interviews with SME employees to verify that items are interpreted as theoretically intended; (c) performing independent-sample exploratory factor analysis prior to confirmatory analysis to determine whether a two-factor, one-factor, or hierarchical structure best represents the empirical data; and (d) examining the two dimensions in separate moderation models—as was done supplementarily in the present study—to document the unique moderating contribution of each dimension before proceeding to joint modeling. Only through such a development process can the theoretical question of whether instrumental and psychological AI support operate through distinct mechanisms be subjected to rigorous empirical test.

Fourth, the sample was restricted to SME employees who had AI tool use experience or expressed intention to use AI tools in the future. This screening condition, while theoretically justified by the study's focus on the competency conversion process rather than technology adoption per se, introduces a clear selection bias that limits the generalizability of the findings. Specifically, the sample likely overrepresents individuals with relatively favorable attitudes toward AI technology, higher baseline technology self-efficacy, and lower technology anxiety compared with the broader SME employee population. This overrepresentation has several implications for interpreting the results. The mean levels of AI literacy (M = 4.15) may be inflated relative to the general SME workforce, the very strong association between AI literacy and innovative behavior (β = .649) may be attenuated among technology-resistant or technology-naive employees for whom the conversion of AI competency into action faces additional motivational and attitudinal barriers, and the relatively low variance in AI attitudes may have restricted the observable range of moderating effects. Therefore, the findings of this study are most directly applicable to SME employees who have already engaged with or are receptive to AI technology, and should not be generalized to the Korean SME workforce as a whole. Future research should employ probability sampling without AI-use screening to establish population-level estimates and examine whether the identified mechanisms—particularly the mediation through AI literacy and the moderation by organizational support—generalize to employees who have not yet adopted AI tools.

Fifth, because only the single coaching source of the direct supervisor was examined, subsequent research comparing and examining the relative and interactive effects of peer coaching, reverse mentoring, and team coaching climate is warranted. Finally, future research exploring the potential for a curvilinear (inverted-U) effect of AI literacy—whereby excessive AI dependency or excessive critical evaluation beyond a certain threshold may actually decrease innovative behavior—would also be meaningful.

6. Conclusion

This study examined the associations among supervisors' coaching leadership, AI literacy, and innovative behavior, and the moderating role of AI-POS, in a sample of 429 South Korean SME employees with AI tool experience or usage intention. The central finding is that coaching leadership is associated with innovative behavior primarily through its capacity to develop employees' AI literacy rather than through direct supervisory influence: the indirect pathway through AI literacy (β = .258) accounted for approximately 72.9% of the total effect and was approximately 2.7 times larger than the residual direct effect (β = .096). AI literacy itself emerged as the strongest correlate of innovative behavior in the model (β = .649), underscoring that employees' integrated capacity to utilize, critically evaluate, ethically apply, and creatively leverage AI constitutes a core driver of workplace innovation in the current technological environment.

Regarding the moderating role of organizational support, the primary moderation analysis using a unified AI-POS composite confirmed that organizational AI support as a whole significantly strengthens the conversion of AI literacy into innovative behavior (β = .181, $p < .001$), consistent with the AMO framework. The theoretical two-dimension distinction between instrumental and psychological support could not be empirically separated in the present data (CFA inter-factor correlation = 1.000), and supplementary dimension-level analyses indicated that both dimensions independently moderated the AI literacy–innovative behavior relationship when examined in isolation. The question of whether these two forms of support operate through distinct mechanisms awaits investigation with more refined measurement instruments.

The sub-dimension analysis offered a hypothesis-generating observation that, across multiple analytic methods and under conditions of severe multicollinearity, relationship building showed the most stable pattern of associations with AI literacy sub-dimensions. This directionally consistent pattern is theoretically interpretable in terms of referent-power-based psychological safety provision in contexts of intergenerational competence reversal; however, given the extreme inter-correlations among coaching leadership sub-dimensions ($r = .929–.940$) and VIF values exceeding 10, this finding cannot be treated as a confirmed theoretical conclusion. It is offered as a direction for future research rather than as an empirical demonstration that relationship building is the uniquely important dimension.

Taken together, these findings provide preliminary evidence for extending coaching leadership theory and the AMO framework to the AI technology context, employing culturally validated Korean instruments in a resource-constrained SME environment. The most robust and practically actionable conclusions from this study are: (1) coaching leadership contributes to employee innovation primarily by serving as an AI literacy development pathway, which is especially consequential when formal AI training infrastructure is absent; (2) organizational AI support in its entirety—encompassing both resource provision and psychological safety—amplifies the innovation-enabling effects of AI literacy; and (3) the relational dimensions of coaching leadership may deserve particular attention in AI leadership development, pending replication with more refined instruments. These conclusions are offered with the explicit acknowledgment that the cross-sectional, single-source design precludes causal inference, and that future longitudinal and multi-source designs are needed to establish the temporal ordering and directional validity of the proposed mechanisms.

These findings collectively advance the theoretical understanding of how coaching leadership, AI competency, and organizational support interact to enable employee innovation in the AI era. Future research should pursue causal direction verification through longitudinal designs, comparative examination of diverse coaching sources including peer coaching and reverse mentoring, team-level analysis through multilevel modeling, and exploration of potential nonlinear effects of AI literacy on innovative behavior. It is hoped that this study provides foundational empirical evidence for an integrative approach to leadership, organizational support, and competency development aimed at strengthening innovation capacity in SMEs in the AI era.

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