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Responsible AI Leadership and Employee Green Innovative Work Behavior: The Mediating Role of AI Learning Self-Efficacy and the Moderating Role of Environmental Commitment

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Email: aijaz@ukm.edu.pk**ARTICLE INFO****ABSTRACT****Received:**

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Artificial Intelligence (AI) is becoming a more integral component of businesses' operations, which leads to a pertinent sustainability challenge: How can the responsible use of AI be translated into sustainable behavior of employees? Responsible AI symbolization by leaders (L-RAIS) is examined as a predictor of green innovative work behavior (GIWB) and AI learning self-efficacy (AILSE) is explored as a mediator between the two variables. Environmental commitment (EC) is explored as a moderating variable for the relationship between L-RAIS and GIWB. Using partial least squares structural equation modeling (PLS-SEM), the data were gathered from 529 employees of the five conventional commercial banks spread across Pakistan, and tested based on Social Cognitive Theory and Signaling Theory. The results show that L-RAIS has a significant positive effect on AILSE ($\beta = 0.504$, $p < 0.001$) and GIWB ($\beta = 0.307$, $p < 0.001$), while AILSE also positively influences GIWB ($\beta = 0.432$, $p < 0.001$). The partial mediation of the relationship between L-RAIS and GIWB supports the assertion that responsible AI leadership contributes to green innovation, in part by growing their confidence in learning and using AI technologies. Furthermore, EC positively moderates the relationship between AILSE and GIWB ($\beta = 0.136$, $p < 0.001$), suggesting that the more committed employees are to the environment, the stronger the relationship between their confidence in AI and their green innovative behavior. The study advances responsible AI research towards sustainable employee outcomes, and identifies the complementary contribution of responsible leadership, AI related psychological capability, and environmental motivation in the context of sustainable digital transformation. The results can be applied in practice for banks looking to harmonize the implementation of AI, staff training, and environmental sustainability goals.

Introduction

Organizational processes are getting transformed in the era of artificial intelligence (AI), and companies are under greater pressure to become more environmentally friendly (Schwaeke et al., 2025). While AI can help optimize resources, monitor the environment, make decisions, and drive innovation, with the adoption of technology, it does not promise responsible and environmentally positive results. Challenges in verifying outputs of AI are still present, along with appropriate reliance on AI systems, data boundaries, and accountability for decisions made with AI assistance within the organization (Erol et al., 2025). Therefore, the sustainability contribution of AI relies not solely on the technical skills, but also on how leaders ensure that responsible AI principles are embedded in the work practices of their employees. This is especially relevant for the financial sector, where digitalization is fast and growing demands for sustainable finance, climate-risk management and environmentally friendly business operations (Wu et al., 2025). The banking sector in Pakistan is undergoing significant digital transformation and, more recently, regulatory efforts have been made to address financial sustainability, such as the Pakistan Green Taxonomy and the framework for climate-related financial risk management, creating a conducive environment for exploring this nexus (Asdullah et al., 2025). Banks need to not only embrace new technologies but also build up staff skills to help drive responsible, environmentally minded innovation. Among the employee-level outcomes that are relevant in this context, one is specifically called green innovative work behavior (GIWB), defined as generation, promotion and implementation of ideas and practices to enhance environmental sustainability. It is observed that the role of leadership, green human resource management, psychological empowerment and self-efficacy have been documented to play significant role in promoting green innovative behavior (Xu et al., 2026; Khairy et al., 2026). But, new signs point to the fact that digital transformation does not necessarily equate to environmental innovation. If they're to produce any real sustainability benefits, technological capacity must be matched with suitable leadership, psychological attitudes and environmental incentives.

Leadership is thus an especially significant aspect in AI-powered environments (Sposato & Dittmar, 2026). While transformational, responsible, sustainable and green leadership has been well researched, the broad implementation of AI presents a new leadership challenge. Previous research on sustainability has focused on transformational, responsible, sustainable and green leadership, but with the widespread use of AI, a new leadership challenge arises (Al Koliby et al., 2025). There is a growing need for employees to be guided not only on ways to innovate but also on how to use AI responsibly, with verification, human oversight, accountability and reliance. To tackle this, recent research has developed a concept called leader responsible AI symbolization (L-RAIS), which indicates the extent to which employees see their leaders' active role in demonstrating and communicating responsible AI practices (Azam, 2026). These include checks on AI output, informed use of AI recommendations, acknowledging the limitations of the data, and maintaining human responsibility in AI-supported decision making. Existing evidence shows that L-RAIS can boost employee creativity with the use of AI-related self-efficacy (Azam, 2026). However, the stimulatory effect of such leadership signals on the appearance of environmentally oriented innovative behavior is far from being researched. This distinction is significant because they are not synonymous outcomes of general creativity and GIWB. AI can boost productivity, customer service, decision-making, and operational efficiency but doesn't create environmental benefits. Thus, there is no obvious evidence that responsible AI leadership leads to creation of AI related capabilities that are contributing to sustainability goals. This is the first significant gap that is tackled with this study. A second gap relates to the psychological process by which L-RAIS might impact on GIWB. This research follows Social Cognitive Theory and centers on AI learning self-efficacy (AILSE), which represents workers' self-assurance in their capacity to enhance their competence in AI technologies and to learn them. Oksanen et al. (2026) recently validated AI learning self-efficacy with a large multinational sample, offering a solid empirical base to investigate the confidence in AI learning. Acceptable use of AI, guidance for behavior and responsible experimentation can all help to reduce uncertainty in how to use AI and strengthen AILSE. With greater AILSE, staff might be more inclined to delve into the potential of AI, learn new competencies, and use technology to address innovative issues in the workplace, such as environmental concerns. But having a high level of confidence in AI learning is not enough to just account for why workers use their abilities towards environmental goals. High AILSE employees can contribute their knowledge of AI to the fields of productivity, customer analysis, risk management, automation, or other areas that are important to their organizations (Li & Geng, 2026). The present study aims to propose a motivational boundary condition, called environmental commitment (EC). EC is psychological attachment and responsibility of employee for the objective of the environment of an organization (Bangwal et al., 2025). While AILSE measures if employees think they can learn and use AI, EC measures if they wish to use them for environmental improvement. The gap between technological capacity and environmental drive is of particular significance, because digital transformation doesn't necessarily result in sustainable outcomes.

In this context, three research gaps are identified that are addressed by the study. First, while responsible AI research is on the rise, there is not much empirical evidence to explain whether such responsible AI symbolization improves outcomes related to sustainability, like GIWB, for employees. Second, the psychological mechanism of the employee level is not well understood, that connects responsible AI leadership to green innovation. Thirdly, the conditions for the conversion of AI-related capacities

into environmentally beneficial innovation have received relatively little attention. Based on this, this study aims to understand the impact of L-RAIS on GIWB of the employees of the conventional commercial banking sector in Pakistan. Specifically, it explores the direct effect of L-RAIS on GIWB, and the mediating role of AILSE, and the role of EC as a moderator of the relationship between AILSE and GIWB. This study also examines if the indirect effect of L-RAIS on GIWB via AILSE is moderated by environmental commitment.

In summary, this research has four contributions to the literature. First, it expands the body of responsible AI leadership research to look at a specific employee outcome. Second, it makes a contribution to the micro-foundations of sustainable digital transformation by defining AI learning self-efficacy as a technology-specific psychological mechanism; the one that connects leadership with green innovation. Third, it separates technological capability from environmental motivation by adding the concept of environmental commitment as a boundary condition. Last but not least, it takes the research of GIWB into an AI-powered banking environment in a new economy in which digital transformation and sustainability legislation are increasingly evolving at the same time.

Literature Review and Theoretical Foundation

Theoretical Foundation

The proposed framework is mostly based on Social Cognitive Theory (SCT) with some elements of Signaling Theory. SCT describes how humans work in terms of the interaction between environmental factors, cognition, and behavior. One of the key components of SCT is self-efficacy, defined as a person's confidence in their ability to initiate and perform the behaviors necessary to attain the desired results. People with higher efficacy beliefs tend to be more inclined to try hard things, to persevere when facing obstacles, and to try new strategies (Xiao & Zheng, 2025). Leaders are an essential part of employees' social work environment in the present study, and the mechanism by which responsible leadership regarding AI can impact on subsequent innovative behavior is the cognition of AI learning self-efficacy. Signaling Theory adds to this view by offering a way of understanding how actions that are observed communicate information in an uncertain world. Ambiguity around acceptable use of AI, verification of output, data usage and accountability are hallmarks of AI-enabled work (Hosseini Tabaghdehi & Ayaz, 2025). This can be minimized by visibly demonstrating and communicating examples of responsible adoption of AI. These behavioral cues will help employees understand what is acceptable when using AI to work, and can therefore help build employee confidence in learning and using AI. So, integrating the two theories offers a parsimonious explanation of the suggested process: leader responsible AI symbolization acts as salient behavioral cues that affect employees' AI-related efficacy beliefs, which in turn affect green innovative work behavior. Environmental commitment also influences the degree of technological confidence aimed at the environmental goals.

Leader Responsible AI Symbolization

The principles of responsible AI have been traditionally discussed on the basis of fairness, transparency, privacy, accountability, human oversight, and reliability. But the principles themselves do not necessarily have a strong impact on behavior unless employees know how they are to be implemented in their daily work with AI. To solve this implementation issue, Azam (2026) suggested the leader responsible AI symbolization (L-RAIS) which is an employee's sense of a leader's overtly exhibiting and modelling responsible-AI behaviours. Its behavior is verifications of AI created information, reasonable use of AI, not blind trust in AI, and human responsibility for AI-assisted decisions. This construct is especially important as it shifts the focus of responsible AI research from the organizational level to the supervisor-employee level. With time-lagged multi-source data from 617 employees-supervisor dyads in Pakistan and China, Azam (2026) found positive associations of L-RAIS with supervisor-rated employee creativity and that AI-learning related self-efficacy was an important explanatory mechanism. The outcome studied was, however, an overall creativity and not the innovative behavior directed towards the environment. Thus, the potential of leadership to inspire the use of AI capabilities for sustainability innovation by employees is yet to be fully understood.

AI Learning Self-Efficacy

A person's self-efficacy in learning and using AI technologies is called AI learning self-efficacy. The construct is less broad than multidimensional constructs like overall AI literacy and is thus well suited to the analysis of the employee-level cognitive mechanism suggested in this study. Recently, Oksanen et al. (2026) validated the five-item AI Learning Readiness Self-Efficacy scale with 20,173 participants in 12 countries across six continents, which supports the scale's reliability, construct validity, applicability for cross-national use, and measurement stability.

Efficacy beliefs are shaped to an extent by the social setting and behavioral models of individuals, from an SCT perspective. Leaders, who set clear guidelines about responsible uses of AI, can minimize the ambiguity regarding the adoption of AI as a

tool to experiment, and provide employees with tangible examples of the use of AI tools in their working lives (Myszak & Filina-Dawidowicz, 2025). This, in turn, could motivate employees to try new applications of AI, stay with the solution despite being a new tool, and make use of AI solutions more confidently in problem solving. These behaviors are very relevant to innovation, as innovative work is often characterized by experimentation, perseverance, learning and trust in solving non-routine problems. The growing evidence then creates a plausible link between responsible AI leadership signals and the employees' AI learning confidence (Hameed et al., 2026). Less clear is whether this psychological trait can be used as a means by which responsible AI leadership promotes green, as opposed to general, innovative behavior.

Green Innovative Work Behavior

Green innovative work behavior is the deliberate production, promotion and application of new ideas, processes or practices that will benefit the environment. It builds on the traditional concept of innovative work behaviour, adding an environmental goal. GIWB involve identification of processes that save resources, the development of ecologically responsible service practices, the introduction of waste or energy reduction programs, the development of green product or services, and the use of technologies to address environmental issues (Piwowar-Sulej & Iqbal, 2025). Recent evidence confirms the increasing importance of employee-level mechanisms in explaining GIWB (Dahiya, 2025). Green innovative behavior is also one of the factors that have been found to be correlated with green HRM, leadership, green self-efficacy, psychological empowerment, motivation, knowledge sharing, organizational support and workplace environmental norms (Khan et al., 2025). For instance, in China and Pakistan, the recent evidence demonstrated that the green HRM practices can foster the employee GIWB via psychological and organizational mechanisms (Khan et al., 2025). Leadership is a key factor influencing green innovation among employees, with a caveat that the impact of digitalization is not always positive. Other recent studies also indicate that green empowering leadership can positively influence the environmental performance via green motivation and GIWB (Alzadjali et al., 2026). However, the existing research is still not closely related to the recently growing field of responsible-AI leadership. Thus, there is limited understanding about how employees might convert leader signals of responsible AI use into environmentally innovative behavior, specifically via efficacy beliefs regarding AI.

Environmental Commitment

Employee environmental commitment is a psychological phenomenon that is defined as an employee's commitment and sense of responsibility for the environment in the workplace. It goes beyond merely recognizing environmental issues as it is a reflection of how aware of environmental issues an employee is, and how important it becomes to them to take action to protect the environment, such as changing their behavior. Highly stated, environmental commitment has always been linked to favorable outcomes in the workplace from the environment (Karatepe et al., 2025). There is a recent evidence that the organizational environmental practices can contribute to reinforce the employees' commitment to the environment and that the commitment to the environment is closely linked to pro-environmental behavior (Bangwal et al., 2025). However, the study on workplace green norms shows that organizational environmental cues can lead to green innovative work behavior through the mediation of environmental commitment (Elshaer et al., 2026). Environmental commitment is one of the important mechanisms that link ECSR with employee GIWB. Unlike other mediators, environmental commitment is considered as a boundary condition within the proposed model and this is significant. High AI learning self-efficacy does not mean that the employee can use AI for the purpose; it is just the belief that the employee can learn and use AI. The use of AI competencies by employees can enhance productivity, marketing, risk management, customer service, or operational efficiency, but it does not necessarily result in environmental improvements. Those most committed to the environment, however, are likely to turn their technological capacities towards the environment and towards sustainability-related opportunities. Environmental commitment can then reinforce the transformation of AI capability to green innovative action.

Synthesis of the Literature

The literature reveals three streams which have grown more or less independently from one another. The role of leaders in implementing abstract principles of AI in employee behavior is slowly gaining recognition in the responsible-AI literature; the research related to self-efficacy in the field of AI emphasizes that employees' self-efficacy in learning AI is an important psychological resource for implementing responsible-AI principles; and the research in the field of sustainability has shown that leadership, environmental commitment and employee-level cognition are important for the emergence of green innovative behavior. But one thing is not understood, how these streams meet.

The framework includes them through conceptualization, namely the social signal in the form of leader responsible AI symbolization, the cognitive mechanism in the form of AI learning self-efficacy, the sustainability-oriented behavioral outcome in the form of green innovative work behavior, and the motivational boundary condition in the form of environmental commitment. This integration gives the theoretical ground for the formulation of the study hypothesis in the next step.

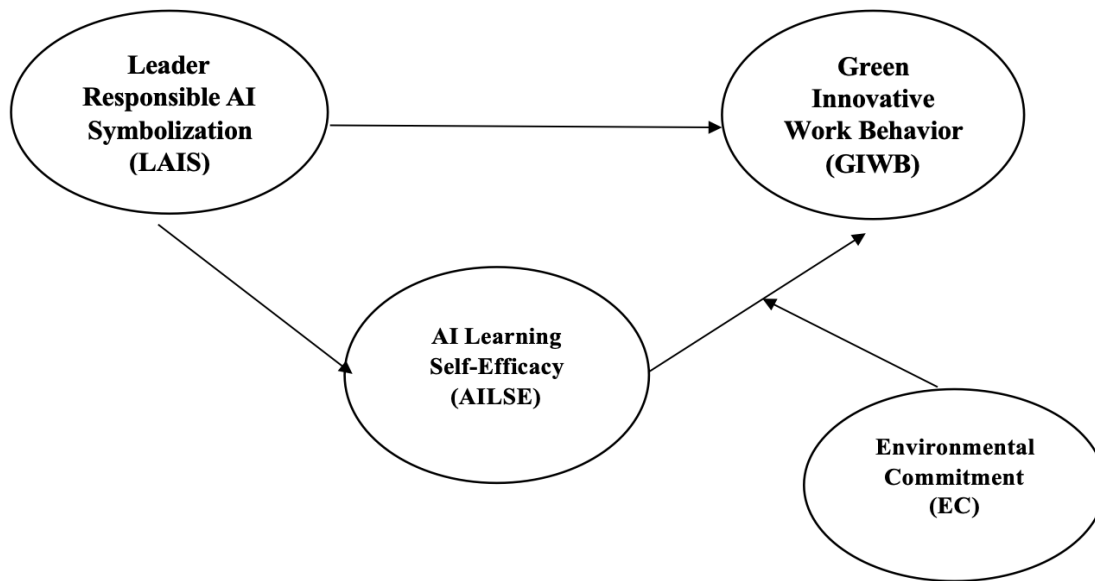


Figure 1: Conceptual Framework

Materials and Methods

Research Design and Context

The design of this study was quantitative research with a cross-sectional design to investigate the relationship between employee green innovative work behavior (GIWB) with leader responsible AI symbolization (L-RAIS) and gain insight into the role of AI learning self-efficacy (AILSE) as a mediating mechanism and environmental commitment (EC) as a moderating condition. The proposed framework looks at the role responsible leadership behaviors in relation to AI in the organizational context on employee outcomes related to sustainability. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used for empirical analysis in the research model because there are direct, mediating, and moderating relationships contained in the model, which is made up of several latent variables (Gudergan et al., 2025). PLS-SEM was chosen as a suitable method for the study because it was prediction-oriented and involved the examination of complex relationships among the latent variables. The analysis was carried out according to the two stage procedure, which includes the evaluation of the measurement model and the evaluation of the structural model. The study has been carried out in the traditional commercial banking sector of Pakistan. This context is deemed suitable on a number of fronts, one being that banks are undergoing a rapid digital transformation, and the other being that sustainability pressures are growing. As a result, financial institutions are leveraging AI for their operations, customer service, risk management, decision-making, and digital banking, and there is growing demand to embed environmental responsibility and sustainable practices into their structures. Employees in commercial banks thus offer a salient context to explore the relationship between responsible AI leadership and innovative behaviors related to sustainability. The participants from these institutions were chosen due to their work being conducted in technology-driven fields where artificial intelligence (AI) use and sustainability efforts are increasingly relevant.

Sampling and Data Collection

The selected conventional commercial banks of Pakistan were selected as the target population of the study and employees of these banks were selected as the target sample. Because a publicly available sampling frame of employees from all of the selected institutions was not available, a non-probability purposive sampling approach was used (Lizarondo et al., 2026). The participants in the survey were chosen because they were working in one of the selected banks and relevant to working contexts related to AI supporting workplace practices or sustainability efforts. The data collection method was the mixed mode survey distribution, which included online and paper questionnaires. The questionnaire was made available to the employees in various branches and departments in print while the online questionnaire was sent by means of Google Forms. This helped to cover a larger area and helped to access respondents from various places in Pakistan. The two survey channels received a total of 577 responses. Following this screening of incomplete responses 529 valid questionnaires were retained for final analysis. An online survey was sent which received 357 usable responses, and 220 paper surveys were sent that yielded 172 paper responses. Thus, the final analytical sample was 529 respondents. The identities of the respondents were not disclosed and their names were not requested for ensuring the confidentiality of the participants. The data gathered were analyzed only in a de-identified manner and no individual respondent or specific organizations could be identified from the results reported.

Measurement and Instrument Development

The questionnaire was designed by adopting pre validated measurement scales in the context of commercial banking in Pakistan. The responsible AI symbolization of leader (L-RAIS) was assessed via five indices reflecting leaders' perceptions of their responsible actions with respect to AI (Azam, 2026). Its construct is based on leaders' observable behaviors related to responsible AI use, such as checking AI information against other sources, using AI tools responsibly, ensuring responsible data usage and having humans take accountability for AI decision-making. AI learning self-efficacy (AILSE) was assessed with five items that reflect the confidence of the employees in understanding, learning and using AI technologies in their work activities effectively (Oksanen et al., 2026). The construct is related to the employees' perceived ability to learn AI content and gain proficiency in new AI technologies. Environmental commitment (EC) was assessed through eight items that reflect employees' psychological attachment, concern and willingness to help the organization achieve its environmental goals (Alcock, 2012). The construct encompasses the level of employees' personal value of environmental programs and their sense of responsibility to support environmental objectives. In order to measure green innovative work behavior (GIWB), six items from the existing innovative work behavior measures were adapted to the context of environmental sustainability (Dahiya, 2025). The construct is related to the actions of employees to develop, advocate, and apply ideas and practices to enhance environmental performance. Each measurement item used the same seven-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). This was a uniform response format that allowed reliable measurement and further analysis with PLS-SEM.

Sample Characteristics

The study used conventional commercial banks in Pakistan and the final sample size was 529 employees of those banks. The respondents were from various career levels and age groups. Employees aged 21–30 years constituted the largest proportion of the sample (39%), followed by respondents aged 31–40 years (28%), 41–50 years (19%), and 51–60 years (14%). For this distribution, there was a mix of newer workers who will likely be working with new technology and older workers who have a lot of knowledge about the organization.

Data Analysis Approach

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the proposed research model. Analysis was conducted in two stages as recommended. To ensure the reliability and validity of the constructs, attention was paid to the measurement model. Secondly, the structure was assessed to examine the hypothesized relationships between the latent variables. The evaluation of the measurement model was conducted with indicator reliability, internal consistency reliability, convergent validity and discriminant validity. The reliability of the indicators was checked using outer loadings, and the internal consistency reliability was checked using the Cronbach's alpha and the composite reliability. The convergent validity was studied using average variance extracted (AVE) and the discriminant validity was studied using heterotrait–monotrait ratio (HTMT). The structural model was evaluated after establishing satisfactory measurement properties. Path coefficients and significance testing were used to examine the direct relations between LRAIS, AILSE and GIWB. The explanatory ability of endogenous constructs was measured by coefficient of determination (R^2) and their predictive relevance and effects size were tested using the procedures of PLS-SEM. The significance of structural relationships was determined using bootstrapping procedures. Mediating role of AILSE was assessed by looking at indirect effect of LRAIS on GIWB. Partial mediation was achieved by considering the direct and indirect effects together. The moderating effect of environmental commitment was explored by examining the interaction between AI learning self-efficacy and environmental commitment. The direction and significance of this interaction effect were explored to see if environmental commitment enhanced the relationship between AILSE and GIWB. Moreover, mediated analyses were performed with moderation to test if the indirect effect of LRAIS on GIWB is stronger at higher and lower levels of environmental commitment.

Ethical Considerations

The study adhered to the standards of ethical conduct in research with human subjects. The survey was self-selected and respondents were told that the information gathered would be for academic purposes only. No personal identifiable data were collected and the information was kept confidential throughout the data collection and analysis. The anonymous survey design was selected to promote truthful answers to questions about leadership behaviors, confidence in AI use and workplace behaviors oriented toward sustainability. The data gathered were only utilized for statistical analysis and reporting of the general results of the research.

Results

Data Analysis Procedure

The theoretical model proposed was tested by applying Partial Least Squares Structural Equation Modeling (PLS-SEM). The analysis was done in two stages, initially the Measurement model was tested and then the Structural model was tested. This study was conducted to examine the reliability of the indicators, the internal consistency reliability of the constructs, the convergent validity, the discriminant validity, the explanatory power of indicators, the path significance, the mediation effect of the indicators, and the moderation effect of the indicators, because they were all reflective first order constructs in the proposed framework. The final data was 529 valid responses from employees of five conventional commercial banks in five different cities of Pakistan. The direct effects of leader responsible AI symbolization (L-RAIS) on AI learning self-efficacy (AILSE), AI learning self-efficacy (AILSE) on green innovative work behavior (GIWB), and environmental commitment (EC) on the direct effects of leader responsible AI symbolization (L-RAIS) on green innovative work behavior (GIWB) were analyzed in the structural model.

Measurement Model Assessment

The measurement model was assessed for its reliability and validity to check the validity of the constructs before testing the structural relationships (Hair et al., 2020). Indicator reliability, internal consistency reliability, convergent validity and discriminant validity were assessed.

Indicator Reliability

The reliability of the indicators was checked using the outer factor loadings. According to PLS-SEM research, the indicators with loadings exceeding the acceptable level are considered good indicators of the latent constructs.

Table 1: Construct Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	AVE
AI Learning Self-Efficacy (AILSE)	0.924	0.925	0.943	0.766
Environmental Commitment (EC)	0.946	0.954	0.955	0.726
Green Innovative Work Behavior (GIWB)	0.934	0.934	0.948	0.752
Leader Responsible AI Symbolization (LRAIS)	0.923	0.924	0.942	0.765

Source: Table by Author.

The internal consistency reliability of all constructs was satisfactory with Cronbach's alpha and composite reliability values above the recommended value of 0.70 (Jarupunphol et al., 2025). In addition, all AVE values were greater than 0.50, thus providing acceptable convergent validity (Cheung et al., 2024).

Results showed good indicator reliability for all constructs. The average loading value of Leader Responsible AI Symbolization was between 0.852 and 0.893. Likewise, the loadings of all the AI Learning Self-Efficacy indicators were strong (between 0.861 and 0.893). The loading value for the indicators Environmental Commitment was acceptable (0.820 to 0.871) and for the indicators Green Innovative Work Behavior was acceptable (0.851 to 0.877). The results for all indicators were above the recommended minimums, which indicates that the items in each measurement scale were good indicators of the respective constructs.

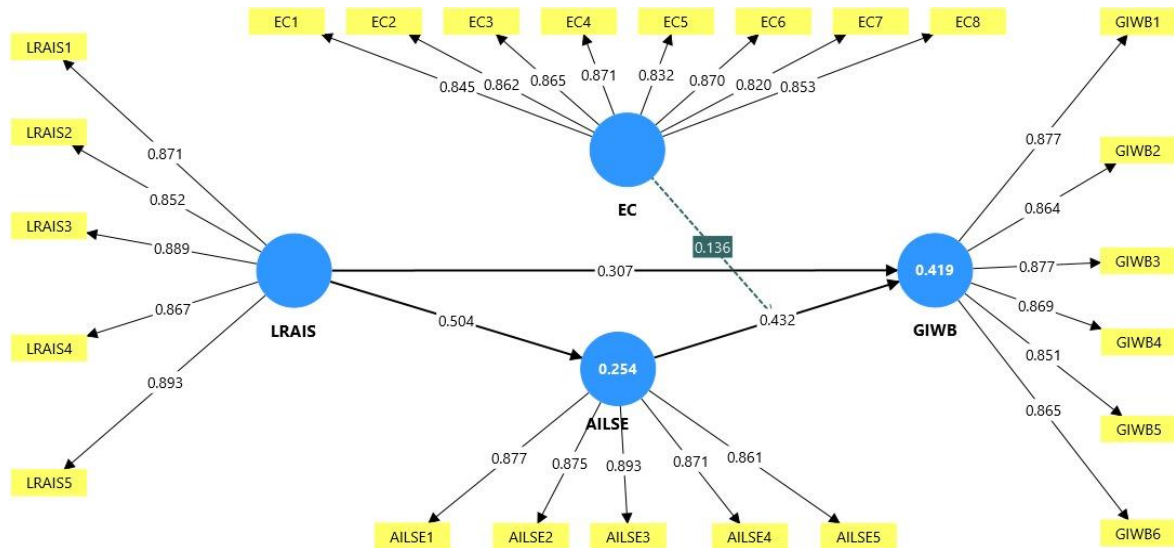


Figure 2. Measurement Model Results and Indicator Loadings

Internal Consistency Reliability and Convergent Validity

Internal consistency reliability and convergent validity were evaluated. Cronbach's alpha and composite reliability was used to assess internal consistency reliability. The reliability of all constructs was satisfactory, with good consistency between the indicators of the measurement.

The results indicated that all the constructs obtained reliability values above 0.7, indicating that the indicators consistently measured the variables they were designed to measure. Average Variance Extracted (AVE) was used to test the convergent validity. All AVE values were higher than the recommended threshold, indicating that the variances in the indicators of each construct are large. Thus, the measurement model met the criterion of internal consistency reliability and convergent validity.

Discriminant Validity

To ensure the constructs were empirically different concepts, the discriminant validity was analyzed and this assessment was done by heterotrait–monotrait ratio criterion (HTMT) (Dirglatmo, 2023).

Table 2: Discriminant Validity Assessment Using HTMT Criterion

Construct Relationship	HTMT Value
EC ↔ AILSE	0.119
GIWB ↔ AILSE	0.615
GIWB ↔ EC	0.112
LRAIS ↔ AILSE	0.545
LRAIS ↔ EC	0.068
LRAIS ↔ GIWB	0.554

Source: Table by Author.

The results of the HTMT were under the conservative cut-off of 0.85, indicating good discriminant validity between all constructs. All constructs were found to have acceptable discriminant validity, which means that leader responsible AI symbolization, AI learning self-efficacy, environmental commitment and green innovative work behavior represent conceptually different dimensions. The findings affirmed that the measurement model is appropriate and pave the way for further assessment of the relationships in the structural model.

Structural Model Assessment

After confirming the quality of the measurements, the structural model was evaluated to see the hypothesized relations between the latent constructs. The evaluation of the structural model comprised of the analysis of explanatory power (R^2), path coefficients, significance levels, mediation and moderation effects (Sharma et al., 2023).

Coefficient of Determination (R^2)

The structural model's explanatory power was evaluated based on the coefficient of determination (R^2).

Table 3. Coefficient of Determination (R^2)

Endogenous Construct	R^2	Adjusted R^2
AI Learning Self-Efficacy (AILSE)	0.254	0.252
Green Innovative Work Behavior (GIWB)	0.419	0.414

Source: Table by Author.

Variance in AI learning self-efficacy was accounted for by 25.4% ($R^2 = 0.254$) of the results from the responsible AI symbolization. This means that certain leadership behaviors related to AI have a significant impact on a people's trust in learning and using AI tools. Furthermore, the combined effects of leader responsible AI symbolization, AI learning self-efficacy, and environmental commitment explained 41.9% of the variance in green innovative work behavior ($R^2 = 0.419$). This shows good explanatory power and suggests that the suggested model adequately explains meaningful variance in employees' innovativeness in sustainability.

Direct Effects and Hypothesis Testing

Bootstrapping procedures were used to address the meaning of structural relationships (Lamberti & La Rocca, 2026). All the hypothesized direct relationships were found to be significant and positive.

Table 4. Structural Model Results and Hypothesis Testing

Hypothesis	Relationship	β	Standard Deviation	t-value	p-value	Result
H1	LRAIS $\rightarrow$ AILSE	0.504	0.0328	15.384	<0.001	Supported
H2	LRAIS $\rightarrow$ GIWB	0.307	0.0395	7.773	<0.001	Supported
H3	AILSE $\rightarrow$ GIWB	0.432	0.0383	11.278	<0.001	Supported
H5	EC $\times$ AILSE $\rightarrow$ GIWB	0.136	0.0286	4.743	<0.001	Supported

Source: Table by Author.

There was a positive effect of Leader Responsible AI Symbolization on AI Learning Self-Efficacy ($\beta = 0.504$, $p < 0.001$). Thus, when employees feel more positive about their leaders' responsible AI-related behaviors, they also have greater belief that they can learn and use AI technologies. H1 was, therefore, supported. Moreover, the Leader Responsible AI Symbolization had a positive and statistically significant impact on Green Innovative Work Behavior ($\beta = 0.307$; $p < 0.001$). This discovery suggests that leadership messages about the importance of responsible AI inspire people to come up with and apply environmentally positive ideas. Hence, H2 was advocated. AI Learning Self-Efficacy also showed a significant positive correlation with Green Innovative Work Behavior ($\beta = 0.432$, $p < 0.001$). The discovery indicates that workers who believe in the learning of AI technologies are more inclined to utilize them for sustainability-related innovation. So, H3 was endorsed.

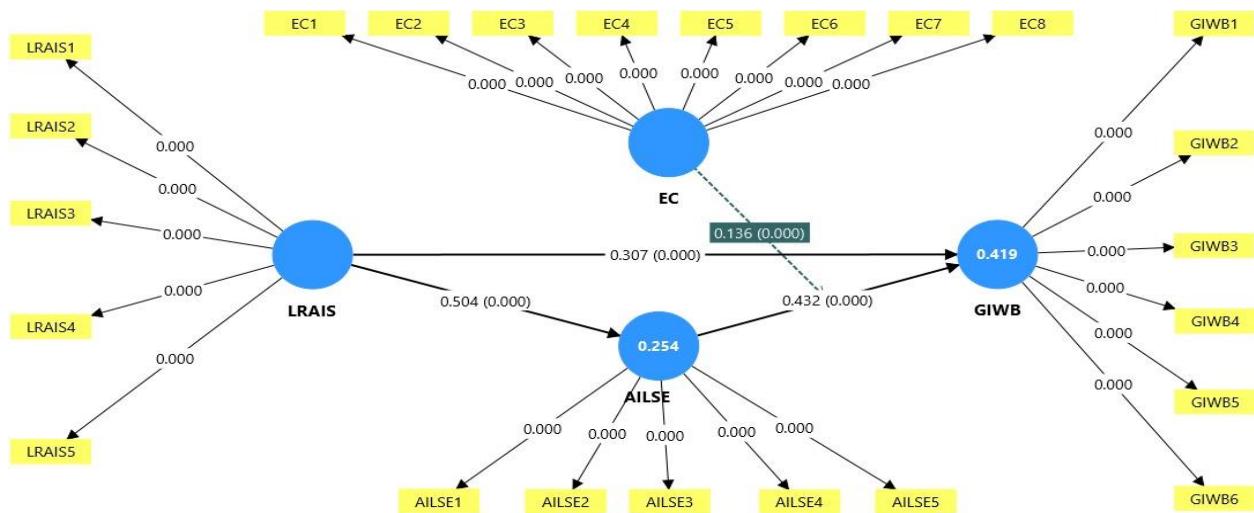


Figure 3. Structural Model Results

Mediation Analysis

The indirect effect of Leader Responsible AI Symbolization on Green Innovative Work Behavior via AI Learning Self-Efficacy was analyzed.

Table 5. Mediation Analysis (Specific Indirect Effect)

Relationship	Indirect Effect (β)	Standard Deviation	t-value	p-value	Decision
LRAIS $\rightarrow$ AILSE $\rightarrow$ GIWB	0.218	0.0243	8.955	<0.001	Supported

Source: Table by Author.

Table 6. Direct Effect After Including Mediator

Relationship	Direct Effect (β)
LRAIS $\rightarrow$ GIWB	0.307

Source: Table by Author.

The indirect pathway was statistically significant and showed that the responsible leadership of AI has a direct effect on the green innovative behavior of employees through its ability to build confidence in learning and using AI technologies. The direct path between Leader Responsible AI Symbolization and Green Innovative Work Behavior continued to be significant when AI Learning Self-Efficacy was added to the model. As a result, the mediation effect was determined as partial mediation. The findings lend weight to the H₄, as responsible AI leadership is shown to be a significant psychological factor in shaping sustainability-focused employee innovation through AI Learning Self-Efficacy.

Moderation Analysis

To see how Environmental Commitment was moderating the relation between AI Learning Self-Efficacy and the outcomes, the moderation effect of Environmental Commitment was explored by creating the interaction effect between AI Learning Self-Efficacy and Environmental Commitment.

Table 7. Moderation Analysis

Relationship	Interaction Effect (β)	Standard Deviation	t-value	p-value	Decision
AILSE $\times$ EC $\rightarrow$ GIWB	0.136	0.0286	4.743	<0.001	Supported

Source: Table by Author.

Interaction term was positive and statistically significant ($\beta = 0.136$, $p < 0.001$). This means that the positive correlation between AI Learning Self-Efficacy and Green Innovative Work Behavior is enhanced by environmental commitment.

Table 8. Simple Slope Analysis

Environmental Commitment Level	Effect of AILSE → GIWB
Low EC (-1 SD)	0.297
Mean EC	0.432
High EC (+1 SD)	0.568

Source: Table by Author.

As employee's environmental commitment increases, the relationship between AI Learning Self-Efficacy and Green Innovative Work Behavior becomes more positive. The combination of confidence in learning AI and environmental commitment is a positive driver of employees' tendency to translate their AI capabilities into innovative actions that benefit the environment. Thus, the support was given for H5.

Moderated Mediation Analysis

Moderated mediation analysis was performed to investigate the mediation of AI Learning Self-Efficacy between Leader Responsible AI Symbolization and Green Innovative Work Behavior at varying levels of Environmental Commitment. The results showed a significant mediation effect for Environmental Commitment on the relationship between the variables. The more employees show commitment to the environment, the more the indirect effect can be strengthened. Thus, the impact of responsible AI leadership on green innovative behavior is indirect and varies with employees' environmental orientation. Therefore, the use of H6 was supported.

Summary of Hypothesis Testing

Hypothesis	Relationship	Result
H1	L-RAIS → AILSE	Supported
H2	L-RAIS → GIWB	Supported
H3	AILSE → GIWB	Supported
H4	AILSE mediates L-RAIS → GIWB	Supported
H5	EC moderates AILSE → GIWB	Supported
H6	Moderated mediation effect	Supported

Source: Table by Author.

Conclusion of Results Section

The overall results support the theoretical framework proposed. The outcomes show that leader responsible AI symbolization has a direct and indirect impact on the AI learning self-efficacy, which, in turn, positively affects the green innovative work behavior. Furthermore, employees' commitment to the environment enhances the level of confidence to innovation aimed at sustainability. Additionally, environmental commitment increases the level of confidence to sustainable innovation among employees. The results underscore the need to combine sustainable AI leadership, employee capacity building in AI, and environmental motivation in organizations seeking sustainable digital transformation.

Discussion

Interpretation of Findings

The current study explored the effect of leader responsible AI symbolization (L-RAIS) on employee green innovative work behavior (GIWB) with the inclusion of two moderating variables, namely AI learning self-efficacy (AILSE) and environmental commitment (EC), and a mediating variable. Based on the theories of Social Cognitive Theory and Signaling Theory, the study suggested that the responsible AI leadership behaviors would serve as meaningful signs that would further boost employees' self-efficacy in learning more about AI technologies and motivate them to innovate for sustainability. The results show that the leader's responsible AI symbolization is an antecedent of green innovative work behavior of employees. This means that ethical and transparent adoption of AI is just one part of responsible AI leadership (Skeja & Sadiku-Dushi, 2026); it also influences employees' use of AI tools to make positive contributions to the environment. This research study focuses on the relevance of responsible AI as a motivating factor for sustainable employee behavior, whereas most previous research on responsible AI has concentrated on governance, accountability and technological reliability. In addition, there is a positive correlation between the

constructs of L-RAIS and AILSE, which suggests that the high level of L-RAIS affects employees' confidence in implementing and learning AI technologies. When leaders model responsible AI practices, promote the human oversight of AI tools, and encourage responsible AI usage, employees feel less uncertain and more confident when working with AI (Deb Biswas & Sengupta, 2026). The discovery is consistent with Signaling Theory and shows that employees are shaped by cues of responsible leadership behaviors as indicators of acceptable technology-related behaviors (Tariq et al., 2025). The results also validated that the self-efficacy of learning using AI is a significant factor in green innovative work behavior. Those who believe they can learn AI technologies are more likely to try out AI-driven solutions and leverage technological capabilities to enhance the workplace and sustainability efforts. This builds upon Social Cognitive Theory by showing that the efficacy beliefs related to the use of AI are an important psychological mechanism for sustainable innovation in the context of digital transformation (Li et al., 2026). The mediation analysis also shows that L-RAIS can be partially explained by the mediation of AILSE. This indicates that there are two pathways to how responsible AI leadership affects green innovation: direct and indirect. Leaders directly influence employee perceptions by their visible implementation of responsible AI practices, and they also increase employees' confidence in using AI technologies to support their work on sustainability issues. Lastly, the mediating role of environmental commitment shows that technological capabilities are not enough to deliver sustainability outcomes. They can have high AI learning confidence but apply this to other aims within their organization. The motivation of employees to use AI knowledge to improve the environment depends on their commitment to the environment. Thus, sustainable digital transformation is a blend of technology and eco-eagerness.

Theoretical Implications

This research builds on the growing body of responsible AI, sustainable AI, and employee innovation studies in a number of ways (Jiang et al., 2026; Tariq et al., 2025). First, it builds on previous responsible AI leadership research by showing its applicability to the outcomes of employees for the environment. Most existing research has focused on responsible AI and issues of ethics, governance, and creativity. This research introduces a new theoretical framework that connects L-RAIS with the concept of green innovative work behavior, thereby broadening the conceptual and theoretical field of research on responsible AI and suggesting responsible AI leadership as a factor for organizational sustainability. Second, the study contributes to the Social Cognitive Theory in that it has identified AI learning self-efficacy as a psychological mechanism specific to the technology. Despite the importance of green self-efficacy and environmental motivation in the field of sustainability research, there has been little focus on workers' self-confidence in developing new technological skills. The results indicate that the psychological resource of employees' belief in learning AI is critical for AI-infused workplaces to sustain innovation. Third, the study elucidates how Responsible AI Principles are manifested in employee behaviors, which is a contribution to Signaling Theory. When AI is in a state of technological uncertainty, workers look to signals from leadership to determine how to interact with AI. Responsible AI symbolization offers clarity on responsibility, verification, and responsible adoption, helping organizations to translate AI governance principles into the actions of employees. Last but not least, this study includes an environmental commitment as a boundary condition, which give a more nuanced understanding of sustainable digital transformation. The results show that positive environmental outcomes are more likely to be achieved if the employees have high environmental commitment, rather than AI capability alone. The contrast between technological capability and sustainability motivation is an important contribution to sustainability research.

Practical Implications

The results offer valuable insights for institutions undertaking transformation initiatives powered by artificial intelligence, especially in the financial sector. The first thing to understand is that there is a need for the active participation of managers in the responsible use of AI (Haque, 2025). Creating AI systems and policies isn't enough because they need to be adopted responsibly, with leaders modeling responsible behaviors through processes that include verifying outputs of AI, keeping humans in the loop and focusing on accountability. This can help to boost employee confidence and responsible use of AI tools. Second, companies should focus on AI learning programs that boost their staff's confidence in learning new skills in AI. Training should incorporate both technical and experiential learning alongside responsible use of AI. Training employees to develop the capacity to build self-efficacy in using artificial intelligence can help them detect and adopt solutions that help them achieve sustainability goals. Third, organizations should focus on embedding AI transformation alongside sustainability, not digitalization and sustainability. Staff should be encouraged to investigate how AI can help them become more efficient with resources, minimize waste in their operations, make environmentally-friendly decisions and improve their environmental performance. Last but not least, organizations need to build their environmental commitment by communicating about sustainability, adopting green organizational practices and providing support to their leaders. For this, it is preferable to raise both technological skills and environmental awareness among employees, as well as to raise the awareness of all employees and of society in general about environmental sensitivity; this will increase the conversion of AI capability into green innovation.

Limitations and Future Research Directions

There are limitations to this study that can lead to further research. Firstly, the cross-sectional design does not allow for causal interpretation. Longitudinal designs may be used in future studies to explore the trajectory of responsible AI leadership and self-efficacy with regard to AI learning. Second, this study used data from the employees themselves. While anonymity was maintained, future studies could include additional data from multiple sources such as supervisor ratings, organizational sustainability metrics, or objective metrics of the use of AI. Thirdly, conventional commercial banks were the focus of the study in Pakistan. Other industries and countries might be studied in the future to determine the generalizability of the proposed framework. Other avenues for future research are the examination of other mechanisms and contextual factors affecting responsible outcomes of AI use for sustainability, such as AI organizational culture and ethical climate, green human resource management, and organizational support for sustainability. Furthermore, other sustainability indicators including green knowledge sharing, sustainable decision-making, and environmental performance could be studied in the future.

Conclusion

Artificial Intelligence's (AI) growing role in organizational processes presents significant opportunities for innovation and sustainability which will depend on the responsible implementation and use of AI. The impact of leader responsible AI symbolization (L-RAIS) on employee green innovative work behavior (GIWB) through a boundary condition of environmental commitment (EC) was examined. This research, based on Social Cognitive Theory and Signaling Theory, offers evidence from the conventional commercial banking field in Pakistan that responsible AI leadership can foster employees' sustainable behavior. The results reveal that L-RAIS has a positive influence on both AILSE and GIWB. Leaders who model responsible AI use such as using AI responsibly, fact-checking AI-generated content, and maintaining human responsibility that offer an actionable set of guidelines for employees to use AI responsibly. This leadership can foster not just responsible technology usage, but also build trust among employees in learning and implementing AI technologies. AILSE was also positively correlated with GIWB, and partially mediated the correlation between L-RAIS with GIWB. This discovery suggests that good AI leadership leads to green innovation, in part by building confidence among staff in developing and utilizing AI skills. Therefore, the psychological preparedness of employees to effectively interact with AI plays a vital role in sustainable digital transformation, in addition to access to AI technologies.

The findings also show that environmental commitment is a positive reinforcement of the relationship between AILSE and GIWB. In general, employees with high AI learning confidence are more likely to apply their capabilities to an innovation that benefits the environment if they also have high levels of commitment to environmental goals. The point here is that AI capability does not equate to environmental motivation; having AI capabilities is not enough to generate sustainability outcomes if they are not tied to environmental goals.

Overall, this research shows that the sustainability value of AI is not only due to technology adoption but also to the convergence of responsible leadership, employee AI learning capability and environmental commitment. Responsible AI leadership can therefore be an important pathfinder in the process of organization's environmental sustainability in the process of digital transformation.

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