AI adoption and employee innovation for sustainability: insights from employee engagement perspectives

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Abstract

Artificial intelligence is increasingly being incorporated into daily work processes in technology companies, thereby creating an environment for sustainability-oriented innovation. This research aims to investigate how employees' intentions to adopt artificial intelligence drive innovative work behavior in support of resource-conserving innovations and digitalized green practices in information technology companies. Employees' engagement is used as a mediator in this process. A model is proposed based on Social Exchange Theory (SET) to explain why supportive organizational contexts drive employees to explore artificial intelligence and translate this experience into practical innovations. A dataset of 450 IT employees is used through purposive sampling. Partial Least Squares Structural Equation Modeling (PLS-SEM) is used to test the proposed relationships. The findings indicate that artificial intelligence adoption intentions have a strong positive relationship with innovative work behavior. Employees' engagement is also found to mediate a significant portion of this relationship. This research contributes to existing theories of sustainability-oriented innovation diffusion by identifying artificial intelligence adoption intentions as an emerging driver of employees' innovation in technology companies.

Keywords: AI Adoption Intention, Employee Engagement, Innovative Work Behavior, Sustainable Innovation, IT Sector

1. Introduction

Sustainability has moved from being a marginal issue to become central to the strategic concerns of technology-driven organizations [1]. The business environment for information technology (IT) companies is marked by fast-paced digitalization, energy-intensive technology, and dynamic innovation cycles. There is growing pressure on information technology companies to optimize resource use, eliminate digital waste, and develop solutions that are consistent with sustainability goals and objectives [2]. On the other hand, information technology companies are also experiencing changes in operational processes and decision-making through the incorporation of artificial intelligence (AI) technology. The integration of sustainability and digital transformation has presented new innovation possibilities [2]. Previous studies have confirmed that sustainability acts as an innovation driver that pushes companies to think and develop resource-efficient solutions. More recent studies on digital transformation have also emphasized technology's impact on innovation processes [5,6]. Yet, much of this literature focuses on organizational or strategic levels, offering limited insight into the employee-level mechanisms through which digital technologies translate into sustainability-supportive innovation [7]. Sustainable innovation ultimately depends on individuals who experiment with tools, identify inefficiencies, and implement improvements [8]. AI technologies provide predictive analytics, automation capabilities, and optimization tools, but their contribution to sustainability-oriented outcomes depends on employees' willingness to adopt and meaningfully use them [3]. This raises an important question: how does AI adoption intention influence innovative work behavior that supports sustainability-oriented improvements?

Although past studies have focused on the topic of digital transformation and innovation, the current study differs in that it conceptualizes artificial intelligence uniquely in terms of its ability to be flexible and predictive in decision augmentation. In this regard, the current study differs from the conventional conceptualization of digital technologies in that it is unique in the ability to learn continuously and recognize patterns on its own. Thus, the present study conceptualizes AI adoption intention in a unique sense in that it is qualitatively different in its influence on the level of employee innovation behavior in sustainability.

This study aims to answer the question of whether employee engagement plays a mediating role in the relationship between AI adoption intention and innovative work behavior (IWB). Based on Social Exchange Theory [9], the present study proposes that AI adoption is positively related to employees' capabilities and opportunities and organizational support, which in turn positively influences employee engagement and ultimately innovative work behavior (IWB).

The aims of the present study are:

1. To examine the relationship between AI adoption intention and innovative work behavior.

2. To investigate the influence of AI adoption intention on employee engagement.

3. To assess the impact of employee engagement on innovative work behavior.

4. To test the mediating role of employee engagement in the relationship between AI adoption intention and innovative work behavior.

This study contributes to the management of innovation in sustainability in that it identifies AI adoption intention as an antecedent of micro-level innovation in sustainability in IT organizations.

2. Literature Review and Hypotheses Development

2.1 Sustainable Innovation and Digital Transformation

Sustainable innovation, as defined, "means the development and implementation of new ideas, processes, or practices that help reduce pressure on the environment and increase long-term value for the organization" [8]. In a technologically advanced environment, sustainable innovation may result from "process optimization, digital efficiency improvements, and resource-aware system innovations" [10]. Digital transformation studies have shown that "technologies like AI can create new possibilities for experimentation and decision-making" [5,6]. However, technological capabilities are not sufficient for sustainable innovation. It requires behavioral activation of employees.

2.2 AI Adoption Intention and Innovative Work Behavior

The intention of adopting AI can be defined as the readiness of the employee to work with AI technologies [11]. Innovative work behavior includes idea generation, idea exploration, idea promotion, and idea implementation [12]. When an employee works with AI technologies, they can access various analytical tools that can encourage innovation in their work processes. Various scholarly articles on digital innovation have shown that technological adoption can encourage the innovative combination of knowledge resources [5]. When an employee is inclined to work with AI technologies, they can use the technologies to automate coding processes using predictive tools, which can encourage sustainability innovation through improved resource utilization [10].

Hypothesis 1: AI adoption intention is positively associated with innovative work behavior.

2.3 AI Adoption Intention and Employee Engagement

Artificial intelligence implementation may be viewed as an expression of organizational investment in employees' ability development. According to Social Exchange Theory (SET), if employees recognize that the organization is investing in valuable resources like AI infrastructure, training programs, and experimentation with technology, it is perceived as support and trust from the organization [9]. This perceived support from the organization evokes a sense of reciprocity in employees, who then respond with positive attitudes and behavior. The initiatives for implementing AI are not only about implementing technology; it is also about investing in employees' ability development. On the other hand, employees respond by showing higher levels of engagement, as indicated by cognitive absorption, social involvement, and emotional commitment [13]. This is the reason why AI adoption intention leads to higher levels of employee engagement, which in turn leads to technological readiness for innovative work behavior [7].

Hypothesis 2: AI adoption intention is positively associated with employee engagement.

2.4 Employee Engagement and Innovative Work Behavior

Attributes of engaged employees include persistence, cognitive flexibility, and proactive problem-solving. Such attributes are significant for the occurrence of innovative work behavior [7]. In the sustainability domain, engaged employees are more alert to inefficiencies and are more engaged in effecting improvements that are aligned to long-term organizational goals [8].

Hypothesis 3: Employee engagement is positively associated with innovative work behavior.

2.5 Mediating Role of Employee Engagement

AI technology might also stimulate innovative behavior through the direct effect of its adoption. However, the conversion of technology readiness into innovation might be influenced by the level of psychological engagement, which mobilizes the required resources for innovation implementation and experimentation [3,7].

Hypothesis 4: Employee engagement mediates the relationship between AI adoption intention and innovative work behavior.

The suggested conceptual framework for the investigation is shown in figure 1.

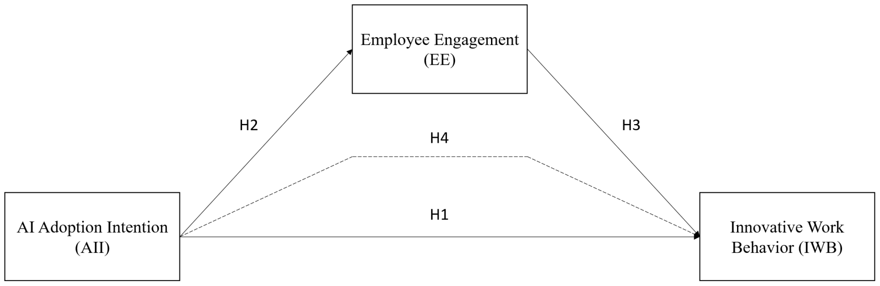

Figure 1: Hypothesized Research Framework

3. Methodology

3.1 Sample and Procedure

This study utilized a deductive cross-sectional quantitative research design, which is appropriate for testing hypotheses in an empirical context. This research utilized a sample of 450 full-time IT professionals in Indian IT firms. Purposive sampling was utilized to ensure that the sample had some level of exposure to AI-enabled systems. The surveys were delivered through electronic means. Voluntariness and confidentiality were ensured. This study checked the potential common method biases using Harman's Single Factor Test. This study revealed that the first component accounted for only 43.95% of the total variance, which is significantly low compared to the required value of 50% or more. This indicates that the common method biases in the dataset were not significant. [14].

3.2 Measurement Instruments

All variables were measured by utilizing validated scales, and all items used a 5-point Likert scale. The measurement of AI adoption intention consists of four items, as proposed by [11], and showed satisfactory reliability (α = 0.803). The measurement of IWB consists of four dimensions, i.e., idea exploration, idea generation, idea championing, and idea implementation, and showed high reliability (α = 0.925), as proposed by [12]. The measurement of EE consists of intellectual, social, and affective dimensions, as proposed by [13], and showed high reliability (α = 0.927).

Although there are no direct measures of sustainability outcomes, IWB was considered as a proxy for sustainability-oriented innovation. In a technology-driven environment, employees are expected to exhibit IWB, and this will be manifested as improvements in processes, efficiency, and optimization of resources.

4. Data Analysis and Results

The analysis was conducted using SmartPLS 4 software to obtain estimates for the PLS-SEM model. PLS-SEM was deemed appropriate due to the model's predicitve focus, mediation effects, and the number of reflective measures for latent variables [15]. The process was divided into two phases: analysis of the measurement model, followed by analysis of the structural model.

4.1 Measurement Model

Internal consistency reliability was evaluated using Cronbach's alpha (CA) and composite reliability (CR). All constructs were above the recommended value of 0.70 (Table 1). The Cronbach's alpha value for AI Adoption Intention (AIAI) was 0.772, for Employee Engagement (EE) was 0.869, and for Innovative Work Behavior (IWB) was 0.927. Composite reliability ranged from

0.776 to 0.929. Therefore, all constructs had strong internal consistency reliability [15]. Convergent validity was evaluated using average variance extracted (AVE), where all AVE values were above 0.560 and below 0.603. Therefore, all constructs had convergent validity since they were able to explain more than half of their own variance. To evaluate indicator reliability, outer loadings were used. Most items had high loadings above 0.70. However, there were slight deviations in two items in EE with low loadings of 0.667 and 0.576. Therefore, all items were retained since they were theoretically sound. To evaluate multicollinearity, variance inflation factor (VIF) was used. The indicator-level VIF ranged from 1.303 to 4.289, which is far below 5. Therefore, there were no concerns of multicollinearity. To evaluate discriminant validity, both the HTMT ratio and the Fornell-Larcker criterion were used. The square roots of AVE were all above correlations with other constructs (Table 2), satisfying the Fornell-Larcker criterion. The HTMT ratio was also below 0.90 (Table 3), which confirmed discriminant validity [15].

Table 1: Measurement Model (Outer loading, Reliability, Convergent Validity, and VIF)

Variables	Constructs/ Dimensions	Item Coding	Factor Loadings	CA	CR	AVE	VIF
AI Adoption Intention (AIAI)		AIAI1	0.756	0.772	0.776	0.589	2.261
		AIAI2	0.774				2.178
		AIAI3	0.817				1.668
		AIAI4	0.719				1.303
Employee Engagement (EE)	Intellectual engagement	EE1	0.713	0.869	0.873	0.560	1.981
		EE2	0.715				2.137
		EE3	0.752				2.055
	Social engagement	EE4	0.743				2.050
		EE5	0.783				2.836
	Affective engagement	EE6	0.813				2.981
		EE7	0.715				1.571
Innovative Work Behavior (IWB)	Idea Exploration	IWB1	0.784	0.927	0.929	0.603	3.146
		IWB2	0.833				2.636
	Idea Generation	IWB3	0.786				4.289
		IWB4	0.759				2.742
		IWB5	0.743				3.206
	Idea Championing	IWB6	0.803				2.306
		IWB7	0.821				3.270
	Idea Implementation	IWB8	0.750				2.709
		IWB9	0.752				3.028
		IWB10	0.725				3.632

Table 2: Fornell-Larcker criterion

CONSTRUCTS	AIAI	EE	IWB
AIAI	0.767		

EE	0.746	0.749	
IWB	0.571	0.609	0.776

Table 3: Discriminant Validity (HTMT ratio)

CONSTRUCTS	AIAI	EE	IWB
AIAI			
EE	0.886		
IWB	0.626	0.663	

4.2 Structural Model Assessment

4.2.1 Model Fit Indices and Predictive Assessment

The structural model was evaluated through R^2, Q^2, and effect sizes (f^2). The R^2 for EE was 0.557, which means that 55.7 percent variance in employee engagement was explained by AI Adoption Intention. The R^2 for IWB was 0.402, which indicates that it had moderate predictive power [15]. Q^2 values for EE and IWB were 0.307 and 0.181, respectively, and were greater than zero, thus validating the predictive relevance (Table 4). The effect sizes (f^2) showed that AI Adoption Intention had a very large effect on EE ($f^2 = 1.258$), a small direct effect on IWB ($f^2 = 0.051$), and EE had a medium effect on IWB ($f^2 = 0.126$). These findings (Table 5) revealed that there were differentiated effects.

Table 4: R^2 and Q^2

CONSTRUCTS	R Square	Q Square
EE	0.557	0.307
IWB	0.402	0.181

4.2.2 Hypothesis Testing

Bootstrapping with resampling was used to test the hypothesised relationships (Figure 2). The direct effect of AI Adoption Intention on IWB was positive and significant ($\beta = 0.263$, $t = 4.270$, $p < 0.001$), supporting H1 (Table 5). AI Adoption Intention had a strong positive impact on Employee Engagement ($\beta = 0.746$, $t = 32.165$, $p < 0.001$), supporting H2. Employee Engagement significantly influenced IWB ($\beta = 0.413$, $t = 5.181$, $p < 0.001$), supporting H3. The mediation analysis revealed a significant indirect effect of AI Adoption Intention on IWB through Employee Engagement ($\beta = 0.308$, $t = 5.087$, $p < 0.001$). Since both direct and indirect effects were significant, Employee Engagement partially mediated the relationship, supporting H4.

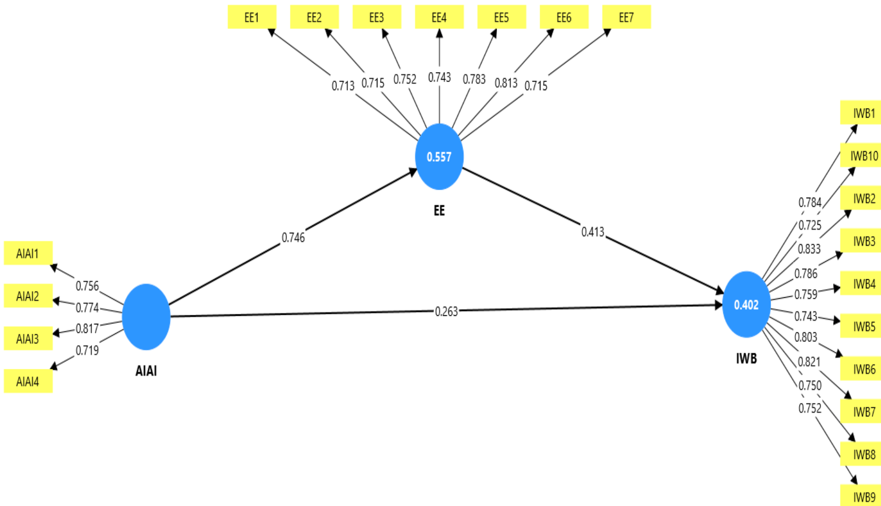

Figure 2: Path Model

Table 5: Path Analysis

Hypothesized path	(β)	(STDEV)	T Statistics	P-Value	Result	F^2	Effect
H1: AIAI → IWB	0.263	0.062	4.270	0.000	Accepted	0.051	Small effect
H2: AIAI → EE	0.746	0.023	32.165	0.000	Accepted	1.258	Very large effect
H3: EE → IWB	0.413	0.080	5.181	0.000	Accepted	0.126	Medium effect
H4: AIAI → EE→IWB	0.308	0.061	5.087	0.000	Accepted	N/A	Partial mediation

5. Discussion

The findings indicate that AI adoption intention positively affects IWB both directly and indirectly through EE. The direct effect is in line with digital innovation scholarship suggesting that advanced technology can expand cognitive recombination and experimentation capacities [5]. In an AI-based environment, predictive analytics and other AI tools may encourage employees to rethink processes, eliminate redundancies, and optimize digital resource allocation, which can contribute to sustainability-oriented innovation [10].

Unlike other digital technologies, which are largely used for enhancing efficiency and automating processes, AI offers an adaptive and predictive functionality that can modify how employees interpret data, recognize areas of inefficiency, and propose solutions. Thus, AI can be considered a cognitive enabler of sustainability-oriented innovation.

Most importantly, AI adoption intention had a strong effect on EE. From the SET perspective, investing in AI-based technology and developing capabilities in AI can be considered an indication of an organization’s long-term commitment to developing employees [9]. Employees, in turn, demonstrate appreciation for such supportive behavior through higher intellectual focus, co-operative involvement, and affective attachment in the organization [7,13].

The partial mediation effect suggests that AI adoption can contribute to innovation through both cognitive augmentation and motivational activation. Although AI can expand cognitive capacities, engagement can activate these capacities. Thus, AI adoption can contribute to innovation through both cognitive augmentation and motivational activation [3].

In terms of sustainability-oriented innovation, these findings suggest that there is a behavioral underpinning of resource-efficient innovation [8]. Although sustainability is not examined in this study, innovative work behavior can involve refinement of processes, elimination of inefficiencies, and better resource utilization. These behaviors represent proximal indicators through which sustainability-oriented improvements can emerge in IT environments.

6. Theoretical Contributions

This study contributes to the literature by focusing specifically on artificial intelligence as a unique technological construct, as opposed to subsuming it as a part of broader digital transformation. As a unique construct, artificial intelligence can be differentiated from traditional digital technologies by its potential for predictive insight generation, complex decision processes, and adaptability to new data environments. As such, this study contributes a more nuanced understanding of how artificial intelligence affects micro-level innovation processes, especially in sustainability-oriented contexts where efficiency and optimization are key. Furthermore, this research also identifies AI adoption intention as a micro-foundational antecedent of sustainability-oriented innovative behavior. While the digital transformation body of knowledge primarily focuses on strategic and structural changes, this research also explores the role of employee-level technological readiness in innovation behaviors, which can contribute to sustainability [6]. Second, this research extends SET to the domain of AI-enabled digital transformation. By conceptualizing AI adoption as an organizational investment in resources, this research clarifies the role of perceived technological support in reciprocal engagement and innovative behaviors [9]. These contributions of SET extend beyond conventional HR domains to emerging technologies. Third, this research connects the domain of sustainability innovation with employee engagement research. While sustainability innovation has been studied at the firm or ecosystem levels [8, 10], there has been limited focus on the psychological mechanisms of sustainability-oriented innovative behaviors. By empirically testing the mediating role of engagement, this research offers a behavioral understanding of digital sustainability transitions.

7. Practical Implications

The implications of the research provide valuable advice to managers who wish to harness the power of AI in the context of sustainability innovation. First and foremost, it is important that AI-related activities be clearly linked to sustainability goals rather than merely emphasized in terms of productivity improvements. For instance, when an IT organization implements AI-based workflow improvements, it can clearly communicate the benefits in terms of reduced energy consumption of the organization's servers or optimized storage options. This helps in creating higher purpose and increasing employee engagement. In addition to this, capability development and the establishment of appropriate employee recognition programs remain important. For instance, when an organization establishes appropriate employee recognition programs in the context of sustainability innovation fueled by AI-based analytics, it can be seen that this helps in creating the right behavior. Similarly, the establishment of appropriate continuous improvement systems in the context of AI-based predictive analytics helps in creating the right innovation outcomes.

8. Limitations and Future Research

The cross-sectional nature of the data restricts causal analysis. Future research can include time-lagged models and measures of green process innovation or sustainable performance to expand the model. In addition, this study uses innovative behavior in the workplace as an instrument for sustainability outcomes, rather than using objective measures of environmental sustainability. Although it is supported by theoretical evidence in past studies in which innovation is used to improve resource efficiency, it is recommended that future research should also be based on objective measures of sustainability, such as energy saving, carbon reduction, and digital resource optimization.

9. Conclusion

Intention to adopt AI is significant in fostering innovative work practices like IWB in IT firms. Employee engagement is also seen as an essential driver that helps translate technological readiness into sustainability-supporting innovation. By explaining how employee engagement through AI fosters resource-conserving innovation and technology-driven green innovation, this study helps understand the microfoundations of sustainable innovation. The study's results highlight that digital transformation initiatives can be sustainability-supporting if employees are psychologically engaged.

Conflicts of Interest The author declares no conflict of interest related to this study.

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