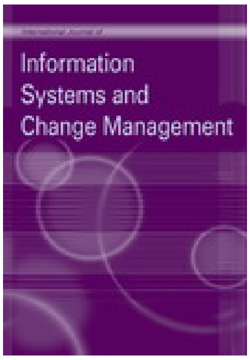

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Stepping into the future: unravelling breakthrough innovations through AI ambidexterity, hybrid intelligence, and transformational leadership

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Stepping into the future: unravelling breakthrough innovations through AI ambidexterity, hybrid intelligence, and transformational leadership

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Abstract: The increasing strategic use of artificial intelligence (AI) in globalisation and market dynamics has resulted in mixed outcomes. Limitations in understanding employees' psychological states towards AI in human resource management (HRM) contribute to this variability. To fill this gap, this study provides an integrated model based on social exchange theory (SET) and resource-based view (RBV) to explain how perceived AI ambidexterity (i.e., routine and innovative use) affects breakthrough innovation engagement. Moreover, it examines hybrid intelligence using mediation and transformational leadership as moderators. Data from 337 high-tech employees in Pakistan was employed for hypotheses testing using partial least square structural equation modelling (PLS-SEM). Findings revealed perceived AI routine and innovative use, and breakthrough innovation engagement's positive relationship, together with hybrid intelligence use mediation. Moreover, transformational leadership moderated perceived AI innovative use and hybrid intelligence use relationships only. By enriching perceived AI ambidexterity in HRM, this study provides significant implications and future research directions.

Keywords: AI; artificial intelligence; perceived artificial intelligence ambidexterity; HRM; human resource management; SET; social exchange theory; RBV; resource-based view; breakthrough innovation engagement; hybrid intelligence; transformational leadership; routine artificial intelligence; innovative artificial intelligence.

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1 Introduction

Nowadays, the highly dynamic business landscape, marked by changing competitive positions, necessitates organisations to innovate for survival and strategic acquisition of competitive advantages (Kistyanto et al., 2022; Stank et al., 2019). Notably, the intersection of globalisation, market internationalisation, and evolving consumer demands drives contemporary organisations to strategically incorporate artificial intelligence (AI) into their operations (Rachinger et al., 2018). AI, an intricate technology that aims for human intelligence stimulation (Glikson and Woolley, 2020), rapidly transforms businesses by broadening their innovative scope. Moreover, International Data Corporation (IDC) highlights the profound impact of AI on economies by anticipating that global AI investments to surge 24.5% annually from $85.3 billion in 2021 to over $204 billion in 2025 (Chowdhury et al., 2023). Notwithstanding, an ambivalent discourse emerges as early adopters report instances of AI investments failing to deliver anticipated business value, contrasting with existing literature emphasising AI's potential to produce valued businesses (Ransbotham et al., 2017). However, studies indicate differences exist, as a consequence of how employees perceive AI implementation (Verma and Singh, 2022). Eventually, organisations struggle to adapt their strategic decision-making processes to AI-induced advances. Thus, it is critical to investigate how employees perceive strategic AI employment impacts their behaviours in service scenarios, especially within high-tech companies, following breakthrough innovations trends (Abbas et al., 2022; Van de Wetering, 2022).

The current AI literature reveals organisational aspirations to automate processes that yield sustainable benefits (Wijayati et al., 2022) embracing the dynamic capabilities lens has characterised organisation's strategic flexibility by AI ambidexterity (i.e., concurrent routine and innovative AI use) in work practices (Van de Wetering, 2022; Verganti et al., 2020). Moreover, such AI proliferation and advancement is redefining HRM (Bussler and Davis, 2002; Lengnick-Hall et al., 2018) from several viewpoints including breakthrough innovation, by staging a crucial part in fostering employee engagement (Huang and Rust, 2018; Jesuthasan, 2017). The ambidextrous AI's innovative and routine use enables proactive execution of a firm's business strategy to innovate (Brock and Von Wangenheim, 2019; Warner and Wäger, 2019). Likewise, employee innovation engagements are collateral to a firm's inclination towards utilisation of any technological opportunity (Ahuja and Morris Lampert, 2001), such as AI systems (Dellermann et al., 2021). Accordingly, researchers have placed substantial focus on how companies should progress business strategies for AI incorporation (Tschang and Almirall, 2021), but extant literature on AI ambidexterity level primarily focuses strategic and technical implementation (Borges et al., 2021; Van de Wetering, 2022). Hence, theoretically informed studies on employees' psychological states in relation to strategic AI integration are scarce, especially in relation to breakthrough innovation engagement (BIE). Therefore, this study seeks to address this knowledge gap by investigating, how employees' perceived AI ambidexterity influences breakthrough innovation engagement among high-tech employees?

AI deployment background demonstrates enhancements in business processes and super human performance are frequently attained by combining AI and employees within a hybrid intelligence environment (Chen et al., 2022). Meanwhile, a growing consensus in the literary circle towards designing collaborative human-machine engineering such as hybrid intelligence exists (Dellermann et al., 2021; Dellermann et al., 2019; Kolfschoten and De Vreede, 2009). In such contexts, the hybrid intelligence approach permits humans AI's predictive power usage while employing their intuition and empathy for making choices basing AI predictions. Hybrid intelligence use (HIU) enhances complementary synthesis of employee's intuition and analysis (Frantz, 2003), and individual learning (Wilkens, 2020), enabling them to spot innovation opportunities. Likewise, Hybrid intelligence promotes psychological ownership that stimulates employee engagement (Dellermann et al., 2019). Similarly, recent studies confirm hybrid intelligence influences self-extension and fosters employee's BIE (Abbas et al., 2022). Accordingly, stating hybrid intelligence systems to pose with AI ambidexterity this study elucidates the psychological phenomena of HIU between perceived AI ambidexterity and BIE.

Furthermore, a leader's influence is crucial for the successful adoption of AI within businesses (Wijayati et al., 2022). Because leadership phenomena encompass a person's capacity to influence other people i.e., followers – in order to attain organisational goals (Mehmood et al., 2020; Mahmood et al., 2019; Nawaz et al., 2022). In addition, scholars call the role of internal resources ascertaining resource-based view (RBV) for developing distinctive (i.e., AI implementation) and hard to imitate capabilities (i.e., leadership) in turbulent, technology-driven business environments (Chowdhury et al., 2023; Mikalef and Gupta, 2021). However, a traditional managerial skill that focuses on efficiency improvement alone does not fit the context (Dhamija et al., 2023). A transformational leader (TL), motivating subordinates to associate with organisational goals and interests to surpass performance expectations (Chaubey et al., 2019; Nawaz et al., 2023; Schuckert et al., 2018), can effectively manage relationships in AI-driven environments. Thus, the present research also attempts to expand the understanding of leadership and AI by exploring, whether transformational leadership moderates the relationship between perceived AI ambidexterity and hybrid intelligence use among high-tech employees?

The present research also aims to contribute in several ways. First, it is amongst the few studies to assess the impact of perceived AI ambidexterity (i.e., concurrent routine and innovative AI use) on BIE in high-tech organisations. Hence, it contributes to the extended work of previous researchers, empirically examining psychological pathways driving employee engagement towards AI-driven innovations with the organisation's internal resources contributing business value (Abbas et al., 2022; Chowdhury et al., 2023; Van de Wetering, 2022). Second, it adds to the scarce literature on perceived AI ambidexterity and BIE in Pakistan's context (Abbas et al., 2022). Besides the scarcity of work, Pakistan's distinct cultural values and high collectivism score (Hofstede, 1984), may help explain this incongruence since reciprocal expectations of being cared about on the part of organisations, leaders, and employees exist in such culture (Nawaz et al., 2022; Zhang et al., 2021). Thus, employees within these cultures are significantly influenced by organisational strategies and leaders, giving considerable attention to an individual's motivation and satisfaction, fundamentals imperative to BIE (Euchner, 2012). Third, it contributes methodology and literature through a holistic perspective of investigating the mediation of the hybrid intelligence approach with the moderation of TL in the nexus of perceived AI ambidexterity and BIE. Therefore, drawing on SET (Homans, 1958) and RBV (Barney, 1991), this study aims to fill the aforementioned gaps in the literature based on the high-tech sector of Pakistan.

The remainder of this paper is organised as follows. The study introduces the formal hypotheses and conceptual framework (See Figure 1), after reviewing the relevant literature. Then, this study describes the methodology followed by data analysis and results. Finally, this paper illuminates implications, and limitations, and outlines directions for future research.

2 Theoretical foundations and literature review

2.1 Social exchange theory (SET)

Social exchange theory has been widely used to study employer-employee, employee-coworker, and employee organisation connections (Cropanzano and Mitchell, 2005; Ilies et al., 2007; Rai, 2013). SET posits that when individuals participate in a sequence of interactions, such as when employers exhibit supportive behaviour towards their employees, a sense of obligation arises from the exchange (Ilies et al., 2007). Subsequently, employees exhibit a reciprocal response by demonstrating a desire to perform effectively and maintain a positive attitude (Cropanzano and Mitchell, 2005). Moreover, SET suggests employer and employee interactions include both economic and psychological exchanges (Cropanzano and Mitchell, 2005). Thus, for high-tech professionals, it can be manifested in standardisation and innovation of employees' work processes brought about by concurrent usage of AI routinely and innovatively (i.e., AI ambidexterity) (Van de Wetering, 2022), freeing humans from repetitive tasks, provoking critical thinking and creativity (Del Giudice et al., 2022; Nawaz et al., 2023), and triggering psychological ownership (Gong et al., 2020). Thus, with perceived AI ambidexterity, an individual's psychological need address can result in reciprocation with HIU and BIE.

2.2 Resource based view (RBV)

Resource based view (RBV), an extensively used theoretical view, explains how resources within organisations help enhance business performance and competitiveness

(Barney, 2001). The firm's RBV states controlling and utilising unique tangible and intangible resources collection provides a competitive edge over competitors (Barney, 1991). Also, existing literature demonstrates RBV's appropriateness in forming hard-to-imitate and distinctive capabilities within turbulent and technology-driven businesses (Mikalef and Gupta, 2021). Thus, consolidating TL as moderator with RBV helps critically understand the role of TL as an internal resource (satisfying inimitable, rare, valuable and nonsubstitutable) in organisations (Ul Haq et al., 2020), for strengthening capabilities, skills, and market position in the adoption, execution, and advancement of AI driven solutions.

2.3 Perceived artificial intelligence ambidexterity, hybrid intelligence, and breakthrough innovation engagement

AI ambidexterity builds on the 'ambidexterity' concept, referring to organisations' exploration and exploitation activities (Luger et al., 2018; March, 1991). Exploration emphasises new business projects and initiatives, while exploitation attention maximising, expanding, and transforming current capabilities with digital innovations (Chen, 2017; O'Reilly and Tushman, 2013). Similarly, Routine AI usage classically associates standardising working activities and routines with AI (Benner and Tushman, 2003). For instance, automated data processing using AI algorithms, AI-based predictive maintenance, and recommendation systems. On the other hand, innovative AI usage denotes novel, emergent, and creative AI applications in employee's work processes (Lee et al., 2015; Wang and Hsieh, 2006), emphasising innovative AI implementation in work processes (Lee et al., 2015). For instance, AI-powered virtual assistants with natural language contextual comprehensions, sentiment analyses, and computer vision using AI algorithms. The AI ambidextrous implementation frees humans from repetitive tasks through exploitation while provoking critical thinking and creativity through exploration (Del Giudice et al., 2022). As AI ambidexterity involves distinctive collaborations between employees and machines (Verganti et al., 2020), it inevitably leads to the formation of perceptions and responses among stakeholders, particularly employees, in relation to organisational strategies and initiatives (Rupp et al., 2006). Consequently, the variations in employees' Behavioural Integration with AI Entities (BIE) cannot be solely attributed to the implementation of AI but also depend on how employees perceive the organisation's AI strategies and efforts.

With continuous AI proliferation, studies reveal that focus on hybrid intelligence design points to a symbiosis for attaining optimal results, leveraging human-AI systems competencies (Dellermann et al., 2021; Dellermann et al., 2019; Jarrahi, 2018; Kolfschoten and De Vreede, 2009). Similarly, Moradi et al. (2019) define hybrid intelligence as "the integration and fusion of (intellectual and non-intellectual) human and machine capabilities in an organised and structured way to perform specific (intellectual and resource intensive) computing tasks". Hybrid intelligence serves a versatile, all-encompassing, and adaptable approach allowing a super collaboration between humans and machines (Abbas et al., 2022; Krinkin et al., 2022). Moreover, research confirms that human-machine symbiosis extends self-capabilities and fosters employees' BIE. Abbas et al. (2022) define BIE based on the work (Shuck et al., 2017): "a process of engaging in behaviour designed for the generation and implementation of new ideas, products, processes and services". Thus, employee engagement vitally motivates desirable behaviours, leading to smart work and improved performance (Gilal et al., 2022; Kwon and Kim, 2020).

AI ambidexterity drives innovative AI-centric projects optimising breakthroughs, and pushing frontiers of organisational transformation (Warner and Wäger, 2019). This advancement not only innovates the organisation's operational business processes (Van de Wetering, 2022) but significantly affects work design (Verma and Singh, 2022). In addition, job design also influences technology professionals' innovative work behaviour (Gilal et al., 2019a, 2019b; Waschull et al., 2020). Moreover, these AI-enabled job characteristics entail a psychological impact on an individual's inclination towards innovation(Verma and Singh, 2022). Similarly, Fan et al. (2020) state high-tech employees' perceptions of AI-enabled work characteristics may influence IWB variances. Based on the premise and AI-enabled job design characteristics approach of (Verma and Singh, 2022), this study draws on SET to investigate employees' perception of AI ambidexterity's (i.e., concurrent routine and innovative use) influence on work characteristics in terms of perceived AI routine and innovative use to predict the reciprocal impact on HIU and BIE.

2.4 Hypothesis development

2.4.1 Perceived artificial intelligence ambidexterity and hybrid intelligence use

AI ambidexterity facilitates enterprises to organise and mobilise resources, talents, and prior unrelated capabilities. Moreover, AI ambidexterity, i.e., concurrent AI routine and innovative usage, enables organisations to modify and improve their work practices by utilising advanced intelligent tools and algorithms (Verganti et al., 2020). Similarly, Routinised AI use generally standardises activities and work routines by an organisation's AI tools, frameworks, algorithms, and procedures (Benner and Tushman, 2003), offloading lower-skilled tasks to AI, increasing the productivity of high-skill work (Tschang and Almirall, 2021). This opportunity to leave mundane tasks and try more analytical and factual solutions provided by AI ushers employees' AI job autonomy (Jarrahi, 2018). Employees with greater AI-enabled Job autonomy can generate innovative ideas with more job control owing to conscious thinking and logical deliberation using AI-driven data (Verma and Singh, 2022), elements extremely imperative to HIU.

On the other hand, Innovative use of AI involving inventive, creative, and novel implementation in employees' work processes (Carter et al., 2020; Lee et al., 2015; Wang and Hsieh, 2006), influences information processing (Wang et al., 2022). Prior studies suggest innovative use of AI in the workplace improves huge information processing and generates insights for employees; the latter is central to employee's HIU. Also, studies noted that AI-facilitated information processing through intuitive decision-making lowers ambiguity and equivocation for employees (Verma and Singh, 2022). Thus, an organisation's ambidextrous AI usage by exposing work to standardised and novel AI applications improves job focus, decision-making, and data processing for problem-solving. Furthermore, this also fulfils employee's essential self-related needs–efficacy and effectance motivation–that respectively tie psychological ownership (Chen et al., 2019; Gong et al., 2020; Pierce et al., 2003). Prior studies suggest this psychological condition helps employees fulfil their need to belong and contribute to the organisation by reciprocation (Ng and Feldman, 2012). Based on SET, likely such routine and innovative interaction of perceived AI may potentially contribute to employees' investment in a hybrid intelligence approach towards innovation and productivity. Therefore, the study hypothesises the following:

Hypothesis 1: Perceived AI routine use has a significant positive impact on hybrid intelligence use.

Hypothesis 2: Perceived AI innovative use has a significant positive impact on hybrid intelligence use.

2.4.2 Perceived artificial intelligence ambidexterity and breakthrough innovation engagement

AI ambidexterity provides organisations with a foundation to progress, develop scenarios, and AI-driven business strategies supporting commitment to action (Verganti et al., 2020). Existing research shows AI implementation boosts productivity and streamlines organisational procedures and activities (Arslan et al., 2022). Likewise, the stance of AI Ambidexterity's routine use strives to exploit, standardise, and refine incremental AI innovation in an organisation's products and services (Benner and Tushman, 2003). This capitalises the AI-enabled work on determined skills (e.g., critical reasoning, inventiveness, effective communication, and collaboration) and analytical capabilities (Martinez, 2017), requiring employee's innovative ideas and solutions. Previous studies noted that employees in such intellectually challenged situations increasingly employ and enhance their analytical and technical skills (Verma and Singh, 2022), likely contributing to the extent of investment in the job. In addition, Pierce et al. (2001) theorise investment experiences of employees institute psychological ownership, elements stimulating employee engagement (Dellermann et al., 2019).

Moreover, the innovative utilisation of AI, with a focus on novel and resourceful approaches to AI integration into work processes (Lee et al., 2015) has the potential to offer significantly enhanced or entirely new services (Van de Wetering, 2022). Nonetheless, the absence of clear insights into the functioning of various AI applications introduces uncertainty, challenges, and increased complexity for high-tech employees (Verma and Singh, 2022). Interestingly, despite challenges, Fan et al. (2020) noted that engaging in complex AI-enabled tasks fulfils employees' need for competence. In addition, existing literature suggests that the complexity of AI-enabled jobs serves as a driver for synthesising technological knowledge, which fosters innovation among employees (Martinez, 2017). Similarly, innovative AI use improves an organisation's agility and employees' ability to spot and engage in innovation prospects. Thus, skills enrichment and constraints conquered by such AI utilisation may likely urge employees to engage in innovative breakthroughs. Thus, it is hypothesised:

Hypothesis 3: Perceived AI routine use has a significant positive impact on breakthrough innovation engagement.

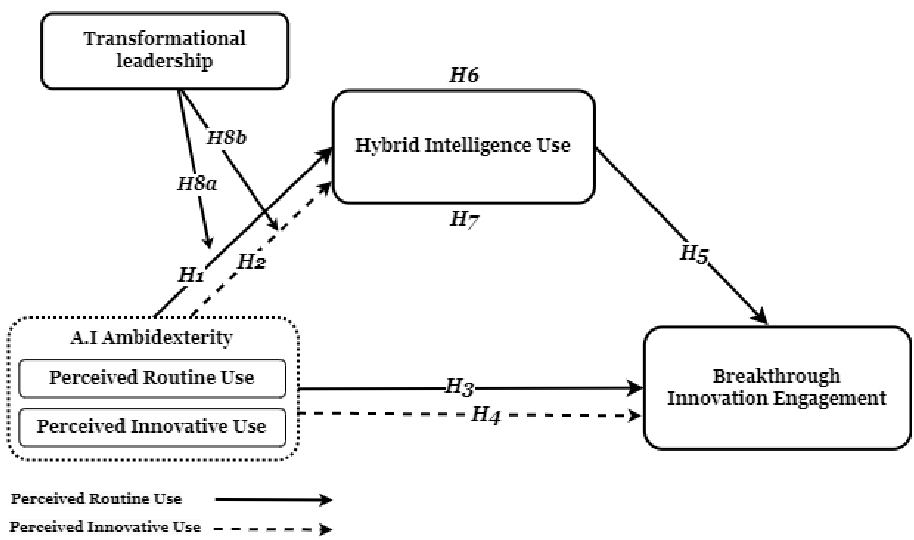
Hypothesis 4: Perceived AI innovative use has a significant positive impact on breakthrough innovation engagement.

2.4.3 Hybrid intelligence use and breakthrough innovation engagement

Within human resource management literature, work on hybrid intelligence is limited. However, a few studies shed light on this emerging topic to explain the conceptual connection between hybrid intelligence and BIE. These studies state, the human AI connection fosters innovation, psychological ownership, and employee engagement in innovative breakthroughs (Abbas et al., 2022). Hybrid intelligence (HI), an integration of machine and human intellect, complements the accomplishment of challenging jobs instead of substituting human cognitive capabilities (Akata et al., 2020). This approach empowers superhuman performance in tasks appearing at the pinnacle of human intellect (Abbas et al., 2022). Meanwhile, employee engagement predicts success better than employee commitment, satisfaction, and job involvement (Rich et al., 2010). Engagement is crucial because breakthrough innovation requires commitment, and people will only fully commit to a future they helped design (Euchner, 2012). Accordingly, taking into account, the hybrid intelligence approach's integration of human and machine cognition for improved processes, knowledge production, psychological ownership, and employee productivity, it is likely to influence BIE. Therefore, it is hypothesised:

> *Hypothesis 5: Hybrid intelligence use has a significant positive impact on breakthrough innovation engagement.*

Figure 1 Conceptual framework



2.4.4 The mediating role of hybrid intelligence use (HIU)

Businesses gain competitive advantages from 'human-machine collaboration' advances and employee's "integrated competencies", that enable productive human-computer interaction (Wilson and Daugherty, 2018). In high-tech companies digital innovations drive employee engagement that transforms employee interaction (Jesuthasan, 2017), such as AI ambidexterity (i.e., concurrent AI routine and innovative usage); capitalising AI integrated work on specialisation of analytical approaches, such as systematic information collecting for reasoning and logical deliberation, so employees spend valuable time building creative innovations from their knowledge (Dwivedi et al., 2021; Lin et al., 2020). In this context, hybrid intelligence enables learning to scan material, merging knowledge from various disciplines, and motivation towards learning (Vrontis et al., 2022). Moreover, the hybrid intelligence approach allows the highest performance by combining human and machine intelligence (Ostheimer et al., 2021).

Furthermore, hybrid intelligence also strengthens the psychological contracts (Hansen and Griep, 2016), acceptability, and trustworthiness towards the organisation; as employee commitment is posed to be strong in the future, they have a part (Abbas et al., 2022). In addition, the hybrid intelligence approach enhances the complementary synthesis of employees' intuition and analysis (Frantz, 2003) and individual learning (Wilkens, 2020), enabling them to spot innovation opportunities. Hybrid intelligence promotes psychological ownership that stimulates employee engagement (Dellermann et al., 2019; Gilal et al., 2022). Recent work confirms hybrid intelligence influences self-extension and fosters employees' BIE (Abbas et al., 2022). Also, studies drawing on SET noted that the opportunity to learn using new technologies diminishes turnover intentions and skill obsolescence, consequently influencing high-tech professionals' commitment to innovation (Harden et al., 2018). Similarly, since perceived innovative and routine use of AI offers improved job focus, decision-making, and data processing for creativity through employee knowledge, a hybrid intelligence approach fosters innovation, psychological ownership, and employee engagement in innovative breakthroughs. Thus, the study hypothesises the following:

Hypothesis 6: Hybrid intelligence use mediates the relationship between perceived AI routine use and breakthrough innovation engagement.

Hypothesis 7: Hybrid intelligence use mediates the relationship between perceived AI innovative use and breakthrough innovation engagement.

2.4.5 The moderating role of transformational leadership (TL)

The technological advances implications are having a significant impact on humans since robots are becoming more significant in organisational and economic areas (Arslan et al., 2022; Coupe, 2019). Nowadays, AI ambidexterity allows businesses to restructure processes and procedures in light of new intelligence-based tools and algorithms (Verganti et al., 2020). Moreover, the encouragement of 'human-machine partnership' and the cultivation of workers' 'fusion abilities' benefits organisations (Wilson and Daugherty, 2018). Accordingly, AI is vital to business process growth, optimisation, and operational flexibility (Kelly et al., 2019; Wang et al., 2022). Furthermore, leaders play a crucial role in the successful adoption of AI inside a business (Wijayati et al., 2022). However, limited studies have supported investigating the moderation of individual differences (in terms of leadership) on technology adoption, as opposed to concentrating solely on their direct effect (Bhatt, 2022). According to Hambrick and Mason (1984), the top leadership (management) portrays an organisation. Because the leadership phenomena encompass a person's capacity to affect others, i.e., followers – in order to accomplish organisational goals (Mahmood et al., 2019). Similarly, the leadership factor affects work climate and how employees perceive their tasks (Azim et al., 2019).

Accordingly, TL, a unique and irreplaceable organisational resource, fosters an innovation climate in firms, which encourages work engagement and strengthens followers' internal motivation, self-efficacy, and creative process engagement (Avolio and Bass, 1995; Chaubey et al., 2019; Mahmood et al., 2019). TL engages individuals in creative activities in an AI-driven hybrid environment by affecting their psychological state (Azim et al., 2019; Matsunaga, 2022). Thus, the study suggests that the TL behaviours (i.e., individual consideration, intellectual stimulation, inspirational motivation, and idealised influence) would inspire, develop, and mentor followers' vision and empowerment such which influences the relationship between perceived AI ambidexterity and hybrid approach. Therefore, the following hypotheses are stated:

> *Hypothesis 8a: Transformational leadership moderates the relationship between perceived AI routine use and hybrid intelligence use such that, the impact is stronger with a high level of transformational leadership.*

> *Hypothesis 8b: Transformational leadership moderates the relationship between perceived AI innovative use and hybrid intelligence use such that, the impact is stronger with a high level of transformational leadership.*

3 Research methodology

3.1 Sampling and data collection

This quantitative research used a non-probability sampling technique with a purposive sampling approach, considered consistent with prior studies research (Gilal et al., 2023; Gong et al., 2023; Wijayati et al., 2022). The technology-intensive sector was chosen for data collection, as previous researchers (Abbas et al., 2022; Kamuriwo et al., 2017), deemed it suitable. Specifically, the present study respondents were employees associated with research and development within innovation-oriented companies (Silva et al., 2017), aiming for competitive advantages, with workflow systems designed to involve AI tools. Data was collected from a variety of high-tech industries and demographically varied organisations in metropolitan cities of Pakistan such as Islamabad, Lahore, and Karachi, thereby increasing the external validity of findings (Fariss and Jones, 2018). Moreover, purposive sampling was employed to align with the research objectives, prioritising respondent confidentiality, while survey questionnaires were self-administered for data collection.

Questionnaire statements were basic and clear; each variable was introduced clearly, and voluntary participation with flexible response time was provided to reduce any biases (Toepoel and Schonlau, 2017). Following Roscoe's (1975) rule of thumb, i.e., most research requires sample sizes of 30–500 (Sekaran and Bougie, 2016), this study distributed 400 questionnaires from December 2022 to March 2023, of which 378 with a response rate of 94% were received back. Similarly, Wijayati et al. (2022) recommend employees of target research institutions with at least one year of affiliation and above to constitute an adequate research sample. Thus, the study deemed responses of individuals with less than one year of experience in current organisations inappropriate. As a result, the present study removed 41 responses for being unsuitable (i.e., incorrect, inappropriate, outlined, and missing values), and 337 questionnaires were considered eligible for further analysis with an acceptable response rate of (337/400) of 84%. As the final number of useable survey responses corresponds to the accepted range of 300–500 recommended by Hair et al. (1998) for structural equation modelling (SEM), thus cause and effect relationships estimation was performed on Smart PLS 4 using the partial least square structural equation modelling (PLS-SEM) technique. PLS-SEM is a widely recognised approach utilised in business research for identifying complicated causal relationships (Gudergan et al., 2008). Table 1 provides a respondent summary and industry affiliation.

Table 1 Respondents profile ($n = 337$)

Respondents particulars	*Number*	*Industry affiliation*	*Number*
Gender		Industry	
Male	272	Information Technology	207
Female	65	Manufacturing and Construction	58
Age group of respondent		Medical and Healthcare	38
20–25 years	31	Automobile and Logistics	34
26–30 years	93	Respondent's tenure in the current organisation	
31–35 years	118	1–3 years	73
36–40 years	57	4–6 years	128
40 above years	38	7–10 years	94
Education of respondent		11 onwards years	42
Graduate	187		
Post Graduate	126		
Others	24		

3.2 Measures

Similar to many prior studies (Pathan et al., 2017; Zhang et al., 2018), this study employed measures from previous research and divided the survey questionnaire into two segments. The first segment focused on respondents' demographics, including gender, age, education, industry, and tenure in the organisation. The second segment examined study variables. Accordingly, Perceived AI routine use was surveyed by adapting three items from the study of Van de Wetering (2022). Perceived AI innovative use was operationalised with three items adapted from Van de Wetering (2022) study. HIU was operationalised with four items adapted from the work of (Abbas et al., 2022). BIE was measured with five items taken from the study of (Abbas et al., 2022). TL was analysed with a seven-item Global TL Scale by (Carless et al., 2000). All items of study variables were reported on a 5-point Likert scale (1 = strongly disagree and 5 = strong agree), with respondents indicating disagreement or agreement with each statement (Sekaran and Bougie, 2016).

3.3 Data analysis method and procedures

This research underscored SEM as a standardised reporting method for enhanced rigour and replicability. Specifically, PLS-SEM stands out as a widely acknowledged and utilised approach across diverse academic domains. Moreover, the PLS approach has been used in some recent studies in AI literature, supporting its suitability in the present investigation (Abbas et al., 2022; Verma and Singh, 2022). Thus, the study predicted the impact of an independent variable on a dependent variable using PLS-SEM. The measurement model of the study was analysed using statistical tools: SmartPLS 4 and SPSS V23. The analytical process encompassed three sequential stages. The initial phase involved the investigation of method bias, followed by confirmatory factor analysis (CFA) and subsequent model evaluation. The final phase comprised a thorough examination of the study's formulated hypotheses

4 Results

4.1 Common method bias (CMB)

This study employed Harman's single-factor analysis to analyse common method bias (CMB). The greater factor accounted for 37.14% of the variance, with no individual component explaining more than 50% variation. Consequently, the investigation concluded that CMB was not a significant concern. Moreover, the measurement model exhibited no issues of multicollinearity, as evidenced by a mean variance inflation factor (VIF) of 2.238 and a maximum VIF value of 3.897, significantly below Neter et al. (1985), recommended cutoff of 5.

4.2 Measurement model validation: CFA

This research analysed the measurement model through discriminant validity, construct reliability, and convergent validity, following Abbas et al. (2022). All measurement items meet the 70% primary research cutoff criterion (Hair et al., 2016), with values ranging from 0.715 to 0.887. Similarly, reliability was assessed using Composite reliability (CR) and Cronbach's alpha (CA). Hair et al. (2017) proposed a minimum threshold for CA and CR values, of 0.6 and 0.7, respectively. This research reported minimal CA and CR values were larger than 0.734 and 0.85, respectively, indicating no reliability issues (See Table 2).

Table 2 Measurement model

Items	*Loadings*	*AVE*	*α*	*Rho_A*	*CR*
Perceived AI routine use (PRU)		0.659	0.738	0.751	0.852
The use of AI has been incorporated into my regular work practices in the organisation	0.844				
The use of AI is pretty much integrated as part of my normal work routine within the organisation	0.862				
The use of AI is now a normal part of my work	0.722				
Perceived AI innovative use (PIU)		0.656	0.734	0.742	0.85
My organisation has discovered new uses of AI to enhance my work performance	0.861				
My organisation has used AI in novel ways to support my work practices	0.846				
My organisation has developed new applications based on AI use to support my work processes	0.715				

Table 2 Measurement model (continued)

Items	*Loadings*	*AVE*	*α*	*Rho_A*	*CR*
Hybrid intelligence use (HIU)		0.665	0.824	0.834	0.884
I routinely use hybrid intelligence support in my job	0.768				
I am excited about how hybrid intelligence can help me with my job	0.862				
I am not worried that hybrid intelligence will make my job more complicated	0.862				
I believe hybrid intelligence will be able to understand my job well enough to help	0.74				
Breakthrough innovation engagement (BIE)		0.583	0.822	0.823	0.875
Working at breakthrough innovative projects has a great deal of personal meaning to me	0.761				
I am really focused on my job when I am working on breakthrough innovative project	0.769				
When working, I think a lot about how I can give my best	0.767				
I really push myself to work beyond what is expected of me	0.757				
I feel strong sense of belongingness to my job	0.764				
Transformational leadership (TL)		0.692	0.889	0.917	0.935
My leader communicates a clear and positive vision of the future	0.867				
My leader treats staff as individuals, supports and encourages their development	0.831				
My leader gives encouragement and recognition to the staff	0.846				
My leader fosters trust, involvement, and cooperation among team members	0.845				
My leader encourages thinking about problems in new ways and questions assumptions	0.887				
My leader is clear about his or her values and practices what he/she preaches	0.883				
My leader instils pride and respect in others and inspires me by being highly competent	0.869				

AVE = Average Variance Extracted, TL = Transformational leadership, CR = Composite Reliability, *α* = Cronbach's alpha.

The near approximation of construct reliability, Rho_A, had indicator readings ranging from 0.742 to 0.917, which exceeded the 70% cutoff and indicated a robust internal consistency for the measurement framework (Hair et al., 2016). All measurement items with loadings exceeding 0.70 demonstrated a substantial impact on their respective variables ($p < 0.001$). Additionally, this study evaluated the construct's convergent validity using average variance extracted (AVE), which showed values ranging from 0.583 to 0.692, exceeding the 0.50 threshold (Hair et al., 2017) and affirming the convergent validity. Moreover, discriminant validity was rigorously assessed using

Fornell Larcker criteria (FLC) (Fornell and Larcker, 1981), Heterotrait monotrait method (HTMT), and cross-loadings (Table 3).

Table 3 Discriminant validity

	FLC					*HTMT*				
Constructs	*BIE*	*HIU*	*PIU*	*PRU*	*TL*	*BIE*	*HIU*	*PIU*	*PRU*	*TL*
BIE	*0.764*									
HIU	0.545	*0.81*				0.653				
PIU	0.571	0.447	*0.81*			0.729	0.572			
PRU	0.678	0.551	0.628	*0.812*		0.862	0.704	0.857		
TL	0.39	0.183	0.418	0.338	*0.861*	0.431	0.19	0.484	0.387	

(a) The diagonals value shows AVE and the bottom cells represent variables squared correlations. (b) HTMT < 1.

FLC involves comparing each construct's AVE value and squared inter-concept coefficient against other variables in the framework. The conditions state that a shared variance between two concepts must not surpass the AVE score of the former (Hair et al., 2016). This study used HTMT ratios < 1 to identify two components, as advised by Hair Jr et al. (2014). The FLC and HTMT scores showed that each construct was distinct and explicitly independent.

4.3 Structural equation modelling

This study proceeded to evaluate the proposed structural framework and associated hypotheses, following the examination of the measurement model. The study framework assigned 35.1% to HI and 52.7% to BIE, underscoring the structural model's robust predictive power. The statistical indicators further affirm the model's reliability, including the Goodness of fit (GOF) at 0.517, exceeding Akter et al. (2011) threshold of 0.36. Additionally, key metrics such as the Avg. path coefficient (APC) at 0.315 ($p < 0.05$), Avg. VIF at 2.238, and Avg. R^2 at 0.439 ($p < 0.05$), along with the adjusted Avg. R^2 at 0.432 ($p < 0.05$), collectively attest to the robustness and goodness of the global fit of the research framework. In addition, to measure the impact of latent predictor constructs on the dependent variable, the effect size (f^2) was calculated (Cohen and Williamson, 1988); to assess the pivotal impact of the theoretical model, characterised by "the prevalence of the phenomena in the population." Cohen and Williamson (1988) explained that the magnitude of the effect is considered small at 0.02, medium at 0.15, and substantial at 0.35. In our model, HIU ($f^2 = 0.068$) and PIU (f^2 value 0.052) exhibit a small impact, while PRU (f^2 value 0.201) revealed a substantial effect. Also, the predictive validity was evaluated using Stone-Geisser Q^2, where values of Q^2 greater than zero establishes the predictive validity of the structural framework (Roldán and Sánchez-Franco, 2012). Notably, this study revealed Q^2 estimates of 0.317 for HIU and 0.472 for BIE, affirming a robust level of predictive validity (See Table 4).

Table 4 Structural model

Goodness of fit statistics, predictive indices and R^2			
Fit indices		*Obtained value*	*p value/Recommended value*
APC		0.315	<0.05
AR^2		0.439	<0.05
AAR^2		0.432	<0.05
AVIF		2.238	<5
GOF		0.517	>0.36
Predictive indices		*BIE*	*HIU*
R^2		0.527	0.351
R^2 *adjusted*		0.522	0.341
Q^2		0.472	0.317
f^2	HIU	*0.068*	
	PIU	*0.051*	
	PRU	*0.201*	

Figure 2 and Table 5 present the findings of hypotheses testing for our model, employing the PLS-SEM technique. The coefficients in these depictions outline the estimated paths for each factor and the relationships among PRU → HIU ($\beta = 0.469$, $T = 7.087$, $p < 0.001$), PIU → HIU ($\beta = 0.257$, $T = 3.498$, $p < 0.001$), PRU → BIE ($\beta = 0.43$, $T = 6.353$, $p < 0.001$), PIU → BIE ($\beta = 0.204$, $T = 3.034$, $p < 0.01$) and HIU → BIE ($\beta = 0.217$, $T = 2.868$, $p < 0.01$). As a result, hypotheses H1, H2, H3, H4, and H5 were supported with statistical significance.

Figure 2 Path analysis results

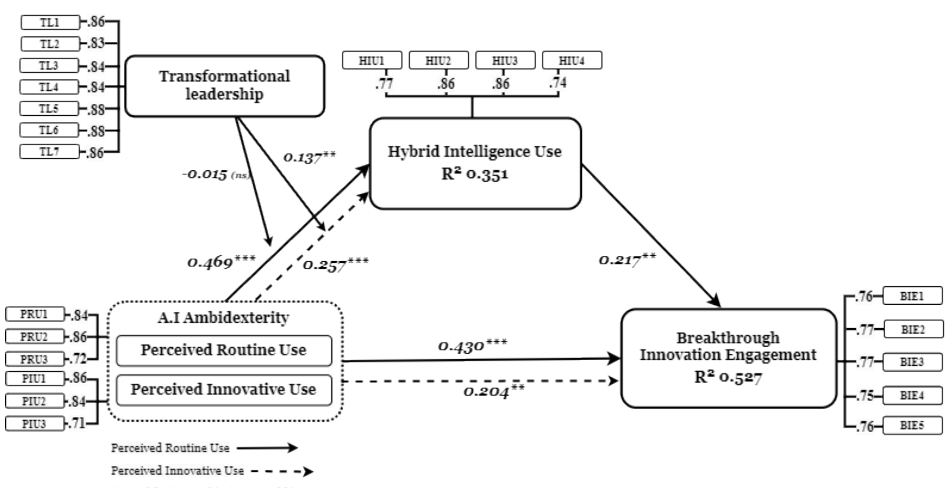


Table 5 Direct effects

Hypotheses	Relationships			Standardised coefficient	Conclusion
	IV	→	*DV*		
Direct effects					
H1	PRU	→	HIU	0.469***	Significant
H2	PIU	→	HIU	0.257***	Significant
H3	PRU	→	BIE	0.43***	Significant
H4	PIU	→	BIE	0.204**	Significant
H5	HIU	→	BIE	0.217**	Significant

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

4.3.1 Results of HIU mediation

The causal relationships of PRU and PIU on BIE may be direct or indirect i.e., the mediation effect of HIU ($\beta = 0.102$, $T = 3.039$, $p < 0.01$) and ($\beta = 0.056$, $T = 2.14$, $p < 0.05$). Thus, H6 and H7 are also accepted (see Table 6).

Table 6 Direct, indirect, and total effects

Mediation| effects				*Direct impact β*	*Indirect impact β*	*Total impact β*
H6	PRU	→	BIE	0.430***	0.102**	0.532***
H7	PIU	→	BIE	0.204**	0.056*	0.260***

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

4.3.2 Results of TL moderation

The moderation results show TL moderates direct relationship between PIU and HIU ($\beta = 0.137$, $p < 0.01$, $T = 2.543$, LLCI = 0.04; ULCI = 0.25). However, the moderation was insignificant on the link between PRU and HIU ($\beta = -0.015$, ns, $T = 0.293$, LLCI = 0.11; ULCI = 0.09). As a result, hypothesis H8b is supported only (see Figure 2 and Table 7).

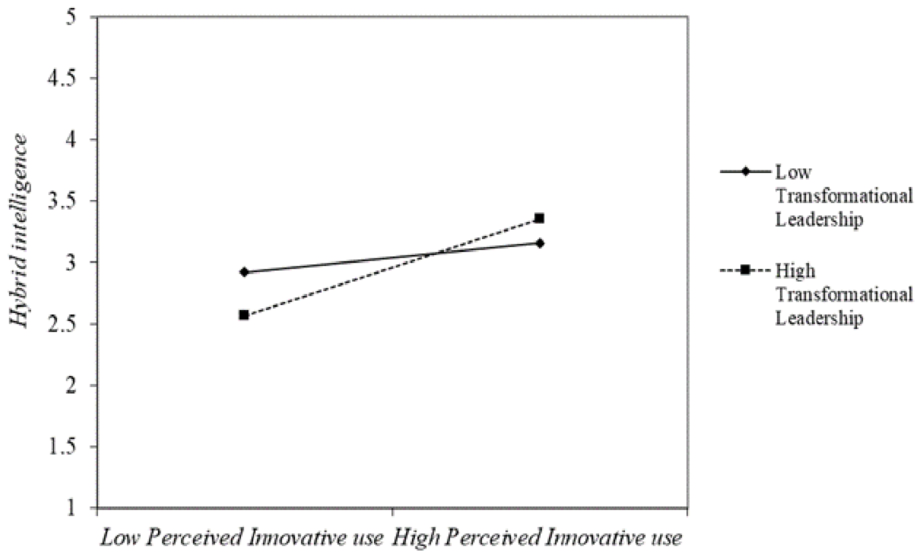
Table 7 Moderating effects

Hypotheses	Relationships			Standardised coefficient	Conclusion
	*IV*Mod*	→	*DV*		
Moderation effects					
H8a	TL × PRU	→	HIU	–0.015 (ns)	Insignificant
H8b	TL × PIU	→	HIU	0.137**	Significant

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

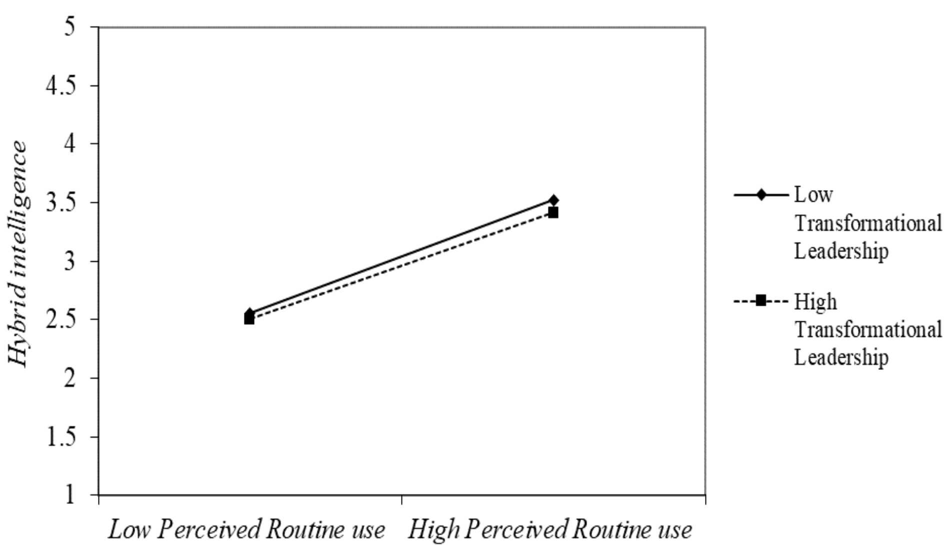
Moreover, the slope analysis presents a better understanding of the nature of moderating effects. Figure 3, presented below, shows the slope analysis for H:8b. The analysis shows that the line is much steeper for high TL; this presents that, at high levels of TL, PIU's impact on HIU is much stronger in comparison to low TL. On the other hand, at low TL, the line tends to straighten, depicting that at a low level of TL, the increase in PIU does not lead to similar changes in the HIU. In conclusion, high TL strengthens the impact of PIU on HIU.

Figure 3 Slope analysis H8b



The slope analysis for H:8a, although insignificant, result in Figure 4 presents the line is much steeper for low TL, in comparison to high TL for PRU; this shows that in such a case at high TL, the increase in PRU does not lead to a similar change in the HIU.

Figure 4 Slope analysis H8a



5 Discussion

The current research investigates mediating and moderating relationships among perceived AI ambidexterity dimensions, namely, HIU, and BIE using a sample of high-tech companies in Pakistan. Additionally, it explores the role of TL as a moderator in AI-driven hybrid settings. The integrated model demonstrates a high level of predictive power in strengthening BIE. The findings reveal that perceived AI routine and innovative use significantly impact BIE. These results align with existing research, as the transformation of high-tech firms by AI advancements (Lin et al., 2020) affects work design and employee appreciation (Verma et al., 2020), leading to innovative work behaviour (Verma and Singh, 2022). Also, studies that noted employees' favourable rational attitudes toward AI were influenced by their belief that AI will support their work (Zhu et al., 2021). The results also revealed that perceived AI routine and innovative use positively impacted HIU. This was supported by prior studies, illuminating contributions of AI understanding, trust, and role clarity towards a symbiotic partnership that leads to collective intelligence (AI-HI) and facilitates employees and organisations to create valued outcomes (Chowdhury et al., 2022).

The results further revealed that HIU positively and significantly influences BIE. This result is backed by extant research, as being a significant contributor to exceptional performance, employees using hybrid intelligence are highly motivated and committed to radically creative enterprises, thereby enhancing their degree of engagement in breakthrough innovation (Abbas et al., 2022). Moreover, findings show a positive mediation of HIU between the relationships of perceived AI routine, innovative use, and BIE. This result aligns with the interpretations of Caputo et al. (2019), suggesting a carefully crafted strategy helps effective collaboration between human intelligence and AI, which unlocks the potential for significant innovative outcomes. These study findings illude the extension of prior work (Abbas et al., 2022; Van de Wetering, 2022), empirically inspecting psychological links illustrating employee innovation engagement. Findings also revealed that TL moderates the relationship between perceived AI innovative use and HIU. Extending the work of Chowdhury et al. (2023), ascertaining resource-based view to elucidate the role of internal resources and TL's impact on employee's psychological state to engage in creative processes within an AI-driven environment (Azim et al., 2019; Mahmood et al., 2019; Matsunaga, 2022), this study presented TL positively moderates the relationship between perceived AI innovative use and HIU. Findings imply that a shift in employees perspective through TL's motivation enables embracing uncertainty and difficulty arising from perceived AI innovative use as a source of hope and personal growth (Chen et al., 2019; Hannah et al., 2016; Mahmood et al., 2019), ultimately fostering collective intelligence.

Furthermore, an insignificant negative moderation of TL between perceived AI routine use and HIU was also revealed. Interestingly, this result contradicts our assumptions and also negates RBV's premise on which the hypothesis was based; however, an alternative interpretation of these findings may be found in TL literature itself, with studies professing the diminishing influence of TL on employee's perception and engagement, as a consequence to additional burdens placed by them. Out of many, a plausible explanation entails, for instance, high standards of performance, requiring increased expression of ideas and more allocations of tasks (Chen et al., 2018; Meng et al., 2020).

6 Theoretical implications

This study contributes several theoretical advances in AI, Hybrid intelligence, and leadership literature. Initially, academic research on the predictive power of perceived AI ambidexterity (i.e., routine and innovative use) in achieving BIE is contributed through a comprehensive examination. Secondly, this study, while utilising SET (Homans, 1958), addresses a paucity of research on the influence of AI's strategic use in theory and practice (Van de Wetering, 2022). This study contributes to the existing knowledge in AI literature by examining the influence of perceived AI routine and innovative use on employee engagement in innovative projects. It aims to illuminate the psychological pathways that drive employee engagement during encounters with cutting-edge technologies (Abbas et al., 2022). Thirdly, the present research adds SET (Homans, 1958) by elucidating 'perceived AI ambidexterity' as a novel perception influencing social exchanges of employer-employee relationships within the context of high-tech innovation and AI adoption. Moreover, by examining the direct and mediated phenomena between perceived AI routine, innovative use, and BIE, this study broadens SET's traditional focus from tangible or emotional benefits to the growing importance of technological resources and benefits in contemporary AI-induced social exchanges. Likewise, the present study through the mediation role of hybrid intelligence contributes to the social exchange framework by explicating that employees' innovation engagement is not solely dependent upon an individual's beliefs and rewards, but also significantly influenced by the integration of hybrid intelligence systems. Lastly, this study addresses research scarcity on an organisation's internal resources facilitating AI embracement (Chowdhury et al., 2023). Hence, drawing upon the RBV (Barney, 1991), this research advocates the role of transformational leadership (TL) in leveraging the impact of employees' perceived AI routine and innovative use to capitalise on the hybrid intelligence approach and BIE. Based on the findings this study adds to RBV by highlighting that TL is not just a comprehensive resource in the AI context; because its effectiveness depends on the specific nature of the resources and skills exchanged with employees.

7 Practical implications

This study bears several noteworthy managerial implications, particularly within the context of technology-driven enterprises. Results highlight that perceived AI routine and innovative use influence HIU, ultimately impacting BIE. Thus, organisations should implement well-crafted AI ambidextrous strategies in such a way that influences employee's belief of AI support in their work, fostering effective collaboration between human intelligence and AI (Caputo et al., 2019). Such effective augmentation with the assistive role of hybrid intelligence encourages employees to extend their analytical and intuitive thinking abilities (Raisamo et al., 2019) ultimately enhancing the contribution of one's self to the development of business strategies and organisational performance (Braganza et al., 2021), through engagement in breakthrough innovation.

The present study examined social exchange relationships in a Pakistani context, ranking high on the collectivism score (Hofstede, 1984). Hence, it is necessary to note that outcomes might be allied to the country's culture. Such Cultures possess certain characteristics, such as a priority towards group harmony and a long-term orientation, emphasising trust and social stability. These characteristics can be advantageous for employee AI adoption, as they encourage a more patient, cohesive, and strategic approach to implementation. This enables organisations and leaders to overcome potential challenges and maximise long-term benefits. Findings also highlight the role of TL in leveraging the relationship between perceived AI innovative use and HIU and the scant yet diminishing influence on the link between perceived AI routine use and HIU. Thus, in order to manage this two-fold influence of TL (Kark et al., 2003), organisations and leaders without violating the specific work regulations should tactically and tactfully apply TL skills for high-tech employees working in AI-driven hybrid environments with supremacy.

8 Limitations and future research directions

This research adds to the corpus of knowledge, but its limitations suggest further research. First, the high-tech industry of Pakistan was focused in the present study. Although AI and Hybrid intelligence research are context-specific, replications in different contexts would strengthen the research model. Other than that, the results present an Asian perspective from a developing country. Further work could be more interesting and generalisable, using the sample from other developing or developed countries from European or Western economies. To analyse the anticipated research framework, this study employed a cross-sectional research design. Future researchers may consider utilising longitudinal, mixed-methods, or multi-level research designs. Additionally, further work can incorporate in-depth interviews, focus groups, and case studies to enhance the understanding of the study framework.

Furthermore, this study limits the social exchange in the employer-employee relationship to AI ambidexterity; future studies can benefit the knowledge base by analysing other organisational variables, like organisational support, innovation climate (Verma and Singh, 2022), and different leadership types. It is paramount to note that fear, uncertainty, and replacement have been highlighted as prominent concerns when employed with cutting-edge technology like AI. Similarly, the perceived substitution crisis has been well documented in the existing AI literature (Verma and Singh, 2022). Thus, further work suggestions to reflect the influence of such variables in the present research paradigm can add to the scarcity of previous practice-based evidence of efficacious strategies in comparable contexts due to the uniqueness of the subject area.

9 Conclusion

The goal of the present work was to analyse the effect of Artificial intelligence ambidexterity on employee breakthrough innovation engagement using data from high tech firms' employees. The extant literature has revealed HRM is redefined, including from an employee's breakthrough innovations standpoint through AI proliferation. This study tested a structural model with perceived AI routine use and perceived AI innovative use as independent variables and HIU as mediating with TL as a moderator to capture the employee's BIE in emerging countries. SEM results presented, both perceived AI routine use, and perceived AI innovative use predicted BIE through direct and via HIU mediation. Moreover, the moderation was statistically significant for perceived AI innovative use and HIU for High TL but it was insignificant yet negative for perceived AI routine use. TL signalled a crucial two-fold influence on employee perceived AI ambidexterity and HIU link. Based on the findings of the present study, we believe to have unveiled and provided a thorough discussion for practitioners and academicians for future research.

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