

The AI Productivity Paradox: When Readiness and Knowledge Sharing Meet Anxiety

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Abstract: As artificial intelligence (AI) becomes increasingly embedded in banking sector; a critical challenge is understanding how organizations can translate employee-oriented investments into productive human-AI collaboration. This study examines how internal marketing turns organizational investment into AI-enabled employee capabilities and productive knowledge, and when this conversion is constrained. A quantitative, cross-sectional survey ($N = 341$) was conducted among employees across operational, supervisory and managerial roles in Pakistan's banking sector who had experience using or interacting with AI-enabled technologies at work. The findings show that internal marketing positively enhances AI readiness, which subsequently strengthens AI-augmented knowledge sharing. This knowledge sharing positively contributes to self-perceived productivity, while AI readiness and AI-augmented knowledge sharing sequentially mediate the relationship between internal marketing and productivity. AI anxiety negatively moderates the relationship between AI-augmented knowledge sharing and self-perceived productivity, weakening this positive association at higher levels of anxiety. The study extends social exchange theory to AI-enabled work by theorizing that AI does not create productivity automatically; rather, its value emerges through an employee-level conversion process that goes beyond AI adoption alone. Importantly, this conversion is psychologically conditioned by AI anxiety, which determines the extent to which AI-enabled knowledge can be translated into productivity gains. The findings can help managers maximize the productive value of AI by embedding role-specific AI development and enabling AI-augmented knowledge-sharing mechanisms within broader reskilling and career-support practices that build employee readiness while reducing anxiety about AI-driven change.

Keywords: Artificial Intelligence, Internal Marketing, AI Readiness, Knowledge Sharing, Employee Productivity

Introduction

Employees constitute a critical source of organizational advantage in knowledge-intensive and rapidly changing business environments because organizational effectiveness increasingly depends on how effectively employees acquire, exchange and apply knowledge (Wang & Noe, 2010). This issue is particularly important in banking, where digital transformation is reshaping service delivery, decision-making and employees' everyday work. In Pakistan, this transformation has become increasingly visible. The State Bank of Pakistan (SBP) reported 9.1 billion retail payment transactions in FY2025, with 88% conducted through digital channels, while mobile banking application users increased from 18.7 million to 24.1 million (State Bank of Pakistan [SBP], 2025). Alongside digitalisation, the growing use of artificial intelligence (AI) is creating new possibilities for automation, information processing, decision support and knowledge-intensive work (Bankins et al., 2024). Consequently, the human capability to adapt to AI-enabled work is becoming as important as technological investment itself.

This transformation raises an important organizational question: *how can organizations prepare employees to effectively leverage AI rather than merely introduce AI technologies into existing work systems?* AI readiness

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encompasses the organizational and human capabilities required to successfully integrate AI (Tehrani et al., 2024), while individual readiness reflects employees' preparedness, confidence and willingness to engage with AI-enabled work (Wang et al., 2026). The importance of this distinction is very relevant in the banking sector, where staff are continually learning and applying knowledge and having to keep up with new technologies. There are some recent studies showing that AI uptake can provide learning opportunities that enable knowledge sharing among employees, suggesting that employees' readiness for AI can be a driver of their ability to leverage the knowledge-related potential of AI (Hu et al., 2025). Internal marketing is one organizational process which could help in preparedness for such a situation. Internal marketing views the employees as internal customers of the company and the employees' behavior as internal marketing of the company towards the internal customers (Ahmed & Rafiq, 2003). Resources for adapting to organisational change can be provided for employees through training and development, internal communication, managerial support and empowerment. In the banking sector, internal marketing has been correlated with positive employee and service experiences (Sharma et al., 2025), and recent studies have found that internal marketing is related to the organizational knowledge-sharing behavior (Nguyen et al., 2024). These practices can thus go beyond traditional employee outcomes in an AI-driven workplace and empower employees to embrace new technologies.

This is in line with the *social exchange theory* (Cropanzano & Mitchell, 2005) which suggests that if an organization treats an employee well, the employee will feel obligated to return the favor and treat the organization favorably. In this way, internal marketing is an investment that an organization makes in the ability and welfare of its employees. In return, employees could become more prepared to use AI, take part in knowledge-related tasks and leverage AI to enhance their performance. AI research in recent years also illustrates the importance of social exchange processes to understand employees' reactions to AI-supported working environments (Khan et al., 2025). *AI readiness* is therefore positioned as the first mechanism through which internal marketing may influence employee outcomes. AI-ready employees are better equipped to understand, accept and integrate AI into their work processes, allowing them to exploit AI beyond simple task automation. However, readiness alone may not generate value unless employees can use AI to enhance how they acquire, process and exchange knowledge. Traditional research establishes knowledge sharing as an important mechanism for organizational learning and performance (Wang & Noe, 2010). In AI-enabled workplaces, intelligent technologies can retrieve information, synthesise knowledge, generate insights and support communication, thereby changing how employees participate in knowledge processes. Accordingly, this study conceptualises *AI-augmented knowledge sharing* as employees' use of AI-enabled capabilities to enhance the acquisition, processing, exchange and application of work-related knowledge. Emerging research indicates that AI can facilitate employee knowledge sharing through enhanced learning opportunities (Hu et al., 2025), while recent research also highlights the changing dynamics of knowledge sharing in AI-enabled workplaces (Zhong & Wang, 2025).

The value of AI-augmented knowledge sharing should ultimately be reflected in employees' work outcomes. Employees who can efficiently access, process and exchange AI-supported knowledge may be better positioned to solve problems and accomplish work tasks, thereby strengthening *self-perceived productivity*. Knowledge sharing has consistently been associated with employee performance through mechanisms such as employee engagement and knowledge utilisation (Engidaw et al., 2024). Recent AI research similarly suggests that knowledge sharing constitutes an important pathway through which AI can enhance employee performance (Khan et al., 2025). Thus, the present study proposes a sequential process in which internal marketing strengthens AI readiness, AI readiness facilitates AI-augmented knowledge sharing, and AI-augmented knowledge sharing enhances employees' perceived productivity. However, the translation of AI-enabled knowledge into productivity may depend on employees' psychological responses to AI. AI can simultaneously provide valuable work resources and generate concerns about technological uncertainty, job security and changing work roles. Research on attitudes towards AI at work demonstrates that employees can experience both positive orientations towards AI and negative reactions such as anxiety

and insecurity (Park et al., 2024). *AI anxiety* may consequently represent an important boundary condition. Employees experiencing greater AI anxiety may become preoccupied with concerns about technological change, job displacement or their ability to keep pace with AI, making it more difficult to translate AI-augmented knowledge into productive work outcomes. Recent research confirms that AI anxiety can negatively influence employees' work-related outcomes (Chen et al., 2025), while evidence from Pakistan indicates that AI-related anxiety can constrain positive employee responses to technological transformation (Nazeer & Ahmad, 2025).

This creates a theoretically meaningful paradox: internal marketing can create the conditions for AI readiness and AI-augmented knowledge sharing, but AI anxiety may determine whether these knowledge resources are translated into productivity. Accordingly, this study asks: how and under what psychological conditions do internal marketing practices translate into employee productivity through AI readiness and AI-augmented knowledge sharing? Drawing on social exchange theory, the study develops a sequential mediation model in which AI readiness and AI-augmented knowledge sharing explain the relationship between internal marketing and self-perceived productivity, while AI anxiety weakens the positive relationship between AI-augmented knowledge sharing and self-perceived productivity. By examining these relationships among employees in Pakistan's banking sector, the study extends internal marketing research into the AI-enabled workplace, advances knowledge-sharing research by recognising the augmenting role of AI and highlights the psychological conditions under which AI-enabled knowledge can generate employee productivity.

Literature Review and Hypotheses

Social Exchange Theory

Social exchange theory provides the overarching theoretical foundation for understanding how organizational practices translate into employee attitudes and behaviours. The theory proposes that social relationships develop through reciprocal exchanges in which favourable treatment generates an expectation of reciprocity (Cropanzano & Mitchell, 2005). Within organizations, employees evaluate the resources and support provided by their employer and may reciprocate through positive attitudes, discretionary behaviours and greater contribution to organizational goals. Internal marketing represents such an organizational investment because training, communication, support and empowerment provide employees with resources that facilitate their development and work effectiveness (Lings & Greenley, 2005). Social exchange theory is particularly relevant to AI-enabled work because organizations increasingly provide employees with technological and developmental resources while employees are expected to acquire new capabilities and adapt their work practices. Recent research has applied this theory to explain positive employee responses to AI, including knowledge sharing and performance (Khan et al., 2025). The theory therefore provides a coherent explanation of the proposed sequence: organizational investment through internal marketing can strengthen AI readiness; AI-ready employees can reciprocate through AI-augmented knowledge sharing; and such knowledge-related contributions can facilitate productive outcomes. At the same time, AI anxiety may increase the perceived psychological costs associated with AI engagement, weakening the conversion of AI-enabled resources into productivity.

Internal Marketing and AI Readiness

Internal marketing encompasses organizational practices through which employees are developed, informed, supported and empowered (Brown, 2025). Its underlying premise is that organizations must attend to their internal market before employees can effectively contribute to external value creation (Gounaris, 2006). Empirical work has identified training, internal communication, leadership, rewards and empowerment among important dimensions of internal marketing (Kaur & Sharma, 2015). These practices are particularly relevant when employees face substantial technological change because organizational support can provide the knowledge and confidence required to adapt to new work demands. AI readiness reflects employees' preparedness and capability to understand and integrate AI into their work. Recent research indicates that

AI readiness involves both technological and human capabilities and represents an important prerequisite for effective AI implementation (Heimberger et al., 2026). Employee-oriented research similarly highlights the importance of AI-related confidence, knowledge and preparedness in developing readiness for AI-enabled work (Ali, 2025; Sameeni & Alvi, 2016). Internal marketing can strengthen these conditions by providing training, communicating technological changes, supporting experimentation and empowering employees to develop new capabilities. From a social exchange theory perspective, organizational investment in employee development creates favourable exchange conditions to which employees can reciprocate through greater preparedness for technological change. Therefore:

H1: Internal marketing has a positive effect on employees' AI readiness.

AI Readiness and AI-Augmented Knowledge Sharing

Knowledge sharing involves the exchange and application of information, expertise and experience among organizational members and represents a fundamental mechanism through which individual knowledge becomes an organizational resource (Argote & Ingram, 2000; Sharma et al., 2025). However, the emergence of AI is changing the way employees acquire, process and exchange knowledge. AI-enabled tools can assist employees in retrieving information, synthesising dispersed knowledge, generating content and supporting problem-solving, thereby augmenting rather than simply replacing employees' knowledge activities (Akhtar, 2022; Zhang et al., 2025). This readiness should therefore shape the ways in which employees can and will use these capabilities to enhance their knowledge-related work. Staff feeling ready to use the AI benefit from an increased likelihood of trying the AI-enabled tools, critically assessing the information produced by AI, and using the AI in their knowledge-sharing processes. AI's ability to facilitate employee knowledge sharing is supported by recent empirical studies, which also show that AI integration can create learning opportunities for employees (Hu et al., 2025). Recent studies also indicate AI-enabled work environments create novel opportunities and challenges related to the utility, sharing and assessment of knowledge (Zhong & Wang, 2025). Therefore, employees should be able to participate in AI-powered knowledge sharing with the ability and confidence provided by AI readiness. In line with the social exchange theory, the employees who gain and build valuable AI-related skills may look back and make an active contribution to the company by sharing their knowledge. Hence:

H2: AI readiness has a positive effect on AI-augmented knowledge sharing.

AI-Augmented Knowledge Sharing and Self-Perceived Productivity

Knowledge sharing enables employees to access expertise, minimize repetitive work and enhance problem solving, all of which help individual employees to perform their jobs better (Mesmer-Magnus & DeChurch, 2009). AI can be utilized in the workplace to improve the value of knowledge sharing as employees can access, combine and apply knowledge more easily and quickly. Thus, AI can be used to augment human skills by expanding the capacity of information processing and boosting decision-making skills of the employees (Akhtar et al., 2022; Jarrahi, 2018). There is recent empirical evidence that backs up this relationship. AI use has been associated with employee performance through knowledge sharing and work engagement (Khan et al., 2025), while experimental evidence demonstrates that generative AI can substantially improve the speed and quality of professional work (Malik et al., 2022; Noy & Zhang, 2023). Research in the Pakistani context has also linked AI with employee productivity through knowledge-sharing mechanisms, although this evidence has primarily examined healthcare employees rather than banking employees (Mushtaq & Akhtar, 2024; Shaikh, 2023). AI-augmented knowledge sharing can therefore provide employees with timely and relevant knowledge that facilitates task completion and problem-solving, enhancing their perceptions of productivity. Under social exchange theory, employees who effectively reciprocate organizational and technological resources through knowledge contributions can derive performance-related benefits from those exchanges. Hence:

H3: AI-augmented knowledge sharing has a positive effect on self-perceived productivity.

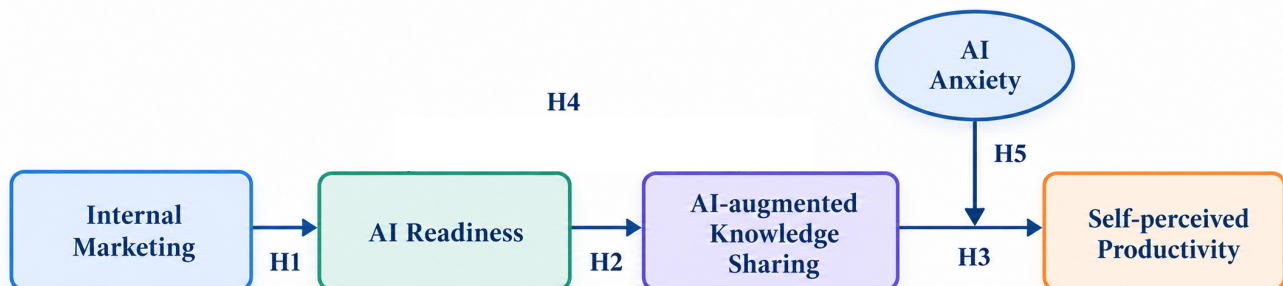
Serial Mediating Role of AI Readiness and AI-Augmented Knowledge Sharing

The preceding relationships suggest that the influence of internal marketing on employee productivity may unfold through a sequential process in which each mechanism enables the next. Internal marketing provides developmental, informational and relational resources that help employees prepare for technological change and develop the confidence and capabilities required to work with AI (Valtonen et al., 2025). This AI readiness, in turn, enables employees to integrate AI more effectively into the acquisition, processing and exchange of work-related knowledge (Li et al., 2025). When such knowledge activities are augmented by AI, employees can access, organise and share knowledge more efficiently, creating resources that can subsequently support task accomplishment and enhance perceived productivity. This sequential logic is consistent with evidence that internal marketing supports knowledge sharing and organizational effectiveness (Yang, 2015) and that its effects on performance can operate through knowledge-oriented mechanisms (Rahimiaghdam, 2020; Sameeni & Qadeer, 2015). More recent AI research likewise indicates that knowledge-sharing mechanisms can connect AI use with employee performance (Khan et al., 2025; Mushtaq & Akhtar, 2025). From a social exchange perspective, organizational investment through internal marketing initiates reciprocity by equipping employees with the resources needed to become AI-ready; employees can then reciprocate through AI-augmented knowledge contributions that enhance their productive capabilities. Thus, the effects of internal marketing on productivity are expected to strengthen as they pass sequentially through AI readiness and AI-augmented knowledge sharing. Therefore:

H4: AI readiness and AI-augmented knowledge sharing sequentially mediate the positive relationship between internal marketing and self-perceived productivity.

Figure 1

Conceptual Framework



Moderating Role of AI Anxiety

Although AI-augmented knowledge sharing can provide valuable resources for employees, its contribution to productivity may depend on employees' psychological responses to AI (Raisch & Krakowski, 2021). AI anxiety encompasses apprehension associated with learning, using and adapting to AI as well as concerns regarding its consequences for employment and work roles (Wang & Wang, 2022). Such anxiety can consume psychological resources and reduce employees' willingness to engage confidently with AI-enabled work. Recent research demonstrates that AI anxiety related to job replacement and learning can undermine employees' work passion (Chen et al., 2025; Sameeni et al., 2022), while research in Pakistan shows that AI anxiety can shape employees' responses to organizational AI transformation (Nazeer & Ahmad, 2025). From a social exchange theory perspective, employees assess not only the benefits but also the costs associated with an exchange relationship. AI-augmented knowledge sharing may provide valuable informational resources, but high AI anxiety can increase perceived risks, uncertainty and psychological costs associated with using those resources. Consequently, employees may possess and share AI-enabled knowledge without being equally capable of converting it into productive work outcomes. Evidence that AI-related risks can condition the positive effects of AI on employee outcomes further supports this boundary-condition

perspective (Khan et al., 2025). Therefore, AI anxiety is expected to weaken the positive relationship between AI-augmented knowledge sharing and self-perceived productivity. Hence:

H5: AI anxiety negatively moderates the relationship between AI-augmented knowledge sharing and self-perceived productivity, such that the positive relationship is weaker when AI anxiety is high.

Methodology

This study employed a quantitative, cross-sectional survey design to examine the proposed relationships in Pakistan's banking sector. The target population comprised employees working across operational, supervisory and managerial roles who had experience using or interacting with AI-enabled technologies in their work. A purposive sampling approach was adopted to ensure that respondents possessed relevant experience for assessing the study constructs. The data were gathered by means of a self-administered questionnaire and participation was voluntary and confidential. During the questionnaire a screening question was added at the outset: 'Have you worked with or used any AI-enabled technology or application in your work? Respondents who answered 'Yes' went on to answer the following measures in the order that they appear below: internal marketing, AI readiness, AI-augmented knowledge sharing, AI anxiety and self-perceived productivity. Demographic and employment data were gathered towards the end of the questionnaire to reduce the chance of demographic questions impacting on the answers to the substantive questions. Of this total 341 responses were eligible for analysis after screening for eligibility and completeness.

The proposed PLS-SEM model was deemed to have sufficiently large sample size. Contemporary methodological guidance recommends determining sample adequacy using statistical power rather than relying solely on the traditional ten-times rule, which provides only a rough minimum guideline (Sameeni et al., 2024a; 2024b). Thus, the final sample of 341 observations yields a significantly larger number of data points to estimate the direct, serial mediation and moderation relations proposed. Partial least squares structural equation modelling (PLS-SEM) was employed to analyse the data, which included assessing the measurement model and testing the hypothesized structural relationships, conducting serial mediation analyses, and examining the moderating effect of AI anxiety.

Measures

The study employed previously established and validated measures, with wording adapted where necessary to reflect the AI-enabled banking context. Internal marketing was assessed with the eight-item scale devised by Kaur and Sharma (2015), which consisted of employee-oriented aspects such as internal communication, training and development, empowerment, rewards, leadership, and organizational support. The seven items used to assess AI readiness were adapted from Wang et al. (2026) and included items related to employees' confidence and cognition, optimism, collaborative learning and working, and comfort in working with AI. AI-augmented knowledge sharing was operationalised by using six items adapted from Wang and Noe (2010) to incorporate the role of AI in employees' acquisition, processing, exchange and application of work-related knowledge. This approach treats AI-augmented knowledge sharing as a context-specific extension of established knowledge-sharing behaviour rather than as an entirely independent, previously established construct. AI anxiety was measured by adapting the AI Anxiety Scale of Wang and Wang (2022), using ten items to the workplace context, capturing employees' concerns regarding AI and its implications for their work. Self-perceived productivity was measured using Bélanger's (1999) four-item scale for employee productivity adapted to the AI-enabled work context. All items were assessed using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

Data Analysis

The demographic profile of the 341 respondents is presented in Table 1. The majority of the respondents were male (60.9%), ranging between 31-40 years of age (37.2%), with a master's degree (48.7%), working at the operational level (41.3%), with most having work experience between 5-10 years (30.2%).

Table 1
Demographic Profile of Respondents (N = 341)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	208	60.9
	Female	133	39.1
Age	18–30 years	74	21.7
	31–40 years	127	37.2
	41–50 years	97	28.5
	Above 50 years	43	12.6
Education	Bachelor's degree	129	37.8
	Master's degree	166	48.7
	MPhil/PhD	46	13.5
Job level	Operational	141	41.3
	Supervisory	116	34.1
	Managerial	84	24.6
Work experience	Less than 5 years	91	26.7
	5–10 years	103	30.2
	11–15 years	71	20.8
	More than 15 years	76	22.3

Measurement Model

The proposed model was examined using Partial Least Squares Structural Equation Modelling (PLS-SEM) through SmartPLS 4. In line with the recommended sequential procedure (Hair et al., 2022), the analysis began with evaluation of the reflective measurement model, followed by assessment of the structural model. The measurement model was examined in terms of indicator reliability, internal consistency, convergent validity and discriminant validity. Standardized outer loadings were used to assess indicator reliability (Table 2), whereas Cronbach's alpha and composite reliability (CR) were examined to establish internal consistency. Convergent validity was determined through average variance extracted (AVE), while discriminant validity was evaluated using the heterotrait–monotrait ratio (HTMT) (Henseler et al., 2015).

Table 2.
Construct Items and Factor Loadings

Construct	Item	Loading
Internal Marketing Kaur and Sharma, 2015	My organisation encourages me to take initiative in using AI-enabled technologies in my work.	0.78
	My organisation trusts me to make appropriate decisions when using AI-enabled technologies.	0.81
	My organisation allows me to use my own judgement when applying AI-enabled technologies to work tasks.	0.78
	My organisation communicates effectively with employees about the use of AI in the workplace.	0.84
	My organisation provides effective channels for employees to discuss AI-related work issues and developments.	0.70
	My organisation provides ongoing training to help employees use AI-enabled technologies effectively.	0.74
	My organisation promotes continuous learning about AI-enabled technologies.	0.71
	Training provided by my organisation helps me apply AI-enabled technologies to my specific work role.	0.81

AI readiness	I feel confident in my ability to understand and use AI-enabled technologies relevant to my work.	0.75
Wang et al. 2026	I have sufficient knowledge to use AI-enabled technologies in my work.	0.76
	I believe AI-enabled technologies can provide useful opportunities in my work.	0.73
	I am optimistic about the benefits of AI for my work.	0.81
	I am able to learn and work collaboratively with AI-enabled technologies.	0.79
	I am willing to collaborate with colleagues when learning to use AI-enabled technologies.	0.76
	I feel comfortable using AI-enabled technologies in my work.	0.75
AI-augmented Knowledge Sharing	I use AI-enabled technologies to share my work-related knowledge with colleagues.	0.81
Wang and Noe, 2010	I use AI-enabled technologies to communicate useful information and expertise to colleagues.	0.76
	I use AI-enabled technologies to help colleagues solve work-related problems.	0.70
	I use AI-enabled technologies to exchange work-related knowledge with colleagues.	0.75
	I use AI-enabled technologies to support the sharing of new ideas and information with colleagues.	0.84
	I use AI-enabled technologies to help organise and communicate knowledge that is useful to my colleagues.	0.81
Self-perceived Productivity	I can perform my job with a high level of effectiveness.	0.71
Bélanger, 1999	I can perform my job with a high level of efficiency.	0.72
	I am able to accomplish my work tasks effectively.	0.73
	I am able to accomplish my work tasks efficiently.	0.75
AI-anxiety	Learning to use AI-enabled technologies for my work makes me anxious.	0.79
Wang and Wang, 2022	I feel anxious when I have to learn new AI-enabled technologies.	0.78
	I feel nervous about keeping up with developments in AI that affect my work.	0.81
	I am afraid that AI-enabled technologies may replace some human jobs in banking.	0.80
	I worry that AI could reduce the need for employees to perform my type of work.	0.81
	I am concerned that AI may make some of my professional skills less valuable.	0.74
	I am concerned that AI-enabled technologies may be misused in the workplace.	0.71
	I am concerned that organisations may become overly dependent on AI.	0.70
	I feel uneasy about relying on AI systems to support important work decisions.	0.73
	I find some AI-enabled technologies difficult to understand or control.	0.77

The retained indicators produced outer loadings between 0.70 and 0.84 (Table 2), demonstrating satisfactory indicator reliability. Cronbach's alpha (α) ranged from 0.76 to 0.92, and composite reliability (CR) values ranged from 0.77 to 0.89, with all coefficients exceeding the recommended 0.70 level (Hair et al., 2022). AVE values fell between 0.54 and 0.59, surpassing the 0.50 criterion and supporting convergent validity.

Table 3

Reliability, Convergent Validity and Discriminant Validity

Sr.no.	Construct	Items	Cronbach's α	Composite Reliability (CR)	AVE
1.	Internal marketing	8	0.88	0.89	0.56
2.	AI readiness	7	0.76	0.77	0.54
3.	AI-augmented knowledge sharing	6	0.81	0.84	0.57
4.	AI anxiety	10	0.92	0.92	0.55
5.	Self-perceived productivity	4	0.79	0.84	0.59

Discriminant validity was subsequently examined using HTMT. The ratios reported in Table 4 ranged from 0.51 to 0.73, remaining below the conservative 0.85 criterion. This provides evidence that the constructs captured empirically distinct concepts (Henseler et al., 2015).

Table 4

Discriminant Validity: Heterotrait-monotrait ratios (HTMT)

Sr.no.	Construct	IM	AIR	AAKS	AIA	SPP
1.	Internal marketing (IM)	—				
2.	AI readiness (AIR)	0.55	—			
3.	AI-augmented knowledge sharing (AAKS)	0.62	0.64	—		
4.	AI anxiety (AIA)	0.57	0.55	0.51	—	
5.	Self-perceived productivity (SPP)	0.64	0.73	0.57	0.51	—

The structural model was then assessed using the relevant explanatory and predictive measures. The model yielded an SRMR of 0.045. The R^2 values ranged from 0.47 to 0.61, while f^2 values ranged from 0.017 to 0.327. In addition, all Q^2 values were greater than zero, providing evidence of predictive relevance. Demographic characteristics were incorporated as control variables in both the direct-effects and mediation analyses.

Hypotheses Testing

The structural model was assessed to examine the proposed direct relationships. Bootstrapping was used to determine the significance of the path coefficients. Table 5 reports the direct effects corresponding to H1-H3 and the interaction effect corresponding to H5. The results indicate that internal marketing significantly predicts AI readiness ($\beta = 0.22$, $p < 0.001$), supporting H1. AI readiness significantly predicts AI-augmented knowledge sharing ($\beta = 0.19$, $p = 0.007$), supporting H2. AI-augmented knowledge sharing significantly predicts self-perceived productivity ($\beta = 0.31$, $p < 0.001$), supporting H3. The interaction between AI-augmented knowledge sharing and AI anxiety is significant ($\beta = 0.27$, $p = 0.003$), supporting H5 and indicating that the positive association between AI-augmented knowledge sharing and self-perceived productivity becomes weaker as AI anxiety increases.

Table 5.
Direct Effects_Self-perceived Productivity

Hypothesis	Relationship	β	SE	t-value	p-value
H1	Internal marketing → AI readiness	0.22	0.06	3.67	< 0.001
H2	AI readiness → AI-augmented knowledge sharing	0.19	0.07	2.71	0.007
H3	AI-augmented knowledge sharing → Self-perceived productivity	0.31	0.05	6.20	< 0.001
H5	AI-augmented knowledge sharing × AI anxiety → Self-perceived productivity	0.27	0.09	3.00	0.003

The serial mediation (Table 6) hypothesis was examined using bootstrapping of the indirect effect. This analysis determines whether internal marketing influences self-perceived productivity through the sequential mechanism of AI readiness and AI-augmented knowledge sharing.

Table 6
Indirect Effect_Self-perceived Productivity

Hypothesis	Indirect pathway	β / Indirect effect	BootSE	t-value	p-value	95% CI
H4	Internal marketing → AI readiness → AI-augmented knowledge sharing → Self-perceived productivity	0.29	0.12	2.42	0.016	[0.06, 0.53]

Internal marketing has a significant indirect effect on self-perceived productivity through the sequential pathway of AI readiness and AI-augmented knowledge sharing (indirect effect = 0.29, 95% CI [0.06, 0.53]). Because the confidence interval does not include zero, the proposed serial mediation is supported, providing evidence that internal marketing contributes to productivity through a sequential process of developing employees' AI readiness and enabling AI-augmented knowledge sharing.

Discussion

The findings provide a coherent explanation of how internal marketing contributes to employee productivity in an AI-enabled banking environment. Rather than indicating a simple relationship between organizational practices and productivity, the results reveal a sequential process in which organizational support first strengthens employees' readiness for AI, this readiness facilitates AI-augmented knowledge sharing, and the resulting knowledge resources contribute to greater self-perceived productivity. At the same time, the negative moderating effect of AI anxiety demonstrates that the productivity benefits of AI-augmented knowledge sharing depend partly on employees' psychological responses to AI. The overall results indicate that the benefits of AI in banking are not just about the technology itself, but through the interaction of organizational preparation, employee capability, knowledge processes and psychological readiness.

The positive relationship between internal marketing and the AI readiness suggests that organizational practices that focus on employees can contribute to the human conditions for AI-enabled work. The traditional focus of internal marketing has been on training, communication, empowerment, support, and employee development, and past studies have demonstrated the importance of internal marketing to knowledge sharing and organizational effectiveness (Rahimiaghdam, 2020; Yang, 2015). The current finding brings this to a technological level. Employees are more likely to grasp and be involved with new technologies if organizations give them information that is relevant to technology, developmental opportunities and supportive working conditions. Such an interpretation aligns with the latest studies that have established that employees' capabilities and organizational conditions are more important to AI readiness than the technology itself (Wang et al., 2026). So, internal marketing seems to offer a framework for the organization to build an

employee AI readiness. The positive association between AI readiness and AI-augmented knowledge sharing suggests that readiness also plays a role in how employees use AI to support knowledge-related work. AI-ready workers are more confident and competent in finding, handling, interpreting and sharing work-related information with AI. This discovery aligns with the recent study by Hu et al. (2025) linking AI adoption to knowledge sharing among employees through providing learning opportunities. It also supports the broader argument that AI should be understood as an augmentation of human knowledge processes rather than simply as an automation technology. If staff are well-informed, AI can help to guide them to access and share information and knowledge with one another and among activities. The finding therefore provides empirical support for viewing AI readiness as an important antecedent of AI-augmented knowledge sharing.

The positive association between AI-augmented knowledge sharing and self-perceived productivity highlights the productivity benefits of AI partly in the knowledge processes. This discovery aligns with studies indicating the impact of knowledge sharing on employee performance (Khan et al., 2025) and evidence that AI can improve employee outcomes through knowledge-related activities. Shaikh (2023), for example, found knowledge sharing to be an important mechanism linking AI-related developments with employee productivity. There are also more recent studies that have suggested that AI-based efforts can enhance employee performance and that the interplay between human and AI can be part of this link (Wan & Jiang, 2026). This current discovery is thus reaffirming a crucial distinction: AI is not always a productivity boost if a worker is just given access to it. Such improvements in productivity are more likely when employees can use AI in areas where valuable knowledge is learned, developed, shared, and utilized. The conclusions of the significant sequential mediation are most comprehensible. The findings show that internal marketing is a driver of productivity through a system of organizational investment that prepares employees, readiness that facilitates knowledge sharing with the help of AI, and knowledge sharing that facilitates productive work. This builds on previous work that found a relationship between internal marketing and knowledge-oriented outcomes (Rahimiaghdam, 2020; Yang, 2015) and recent studies linking AI with knowledge sharing and employee performance (Hu et al., 2025; Khan et al., 2025). Importantly, the result indicates that AI readiness and knowledge sharing augmented by AI are not two stand-alone mechanisms. Their sequential relationship suggests that employees have to be well-prepared to interact with AI before they can effectively integrate AI into their knowledge sharing processes. This is especially relevant in the banking industry, where in the implementation of AI, employees must apply the technological capability and knowledge of the business with professional judgment.

However, it is crucial to recognize that these positive relationships are qualified by AI anxiety, which has a negative moderating effect. The more anxious employees get about AI, the less they seem to be able to translate AI-supported knowledge sharing into perceived productivity. The result aligns with research indicating that employee experiences of AI anxiety negatively impact employee experiences (Chen et al., 2025) and with recent studies on the relationship between AI anxiety and negative outcomes in the workplace (Tong et al., 2025). Furthermore, it aligns with studies showing organization's AI adoption may cause positive and negative knowledge behaviors based on the employees' interpretation of technological change (Zhu et al., 2025). From this standpoint, AI-powered knowledge sharing is a potential resource, while AI anxiety is a psychological cost that can diminish the value employees can get from the resource. The results thus reflect the ambivalence of opportunities and apprehensions in AI work. In summary, the findings reflect AI-powered productivity as a process of capability and psychology. The organizational conditions that enable AI readiness are created through internal marketing; AI readiness allows employees to participate in knowledge sharing in the context of AI; knowledge sharing is a path to productivity; and the extent to which AI knowledge resources translate into productive outcomes is determined by the level of AI anxiety. This is aligned with social exchange theory, as the provision of resources by an organization can be met with employees' capability growth, knowledge sharing, and productive actions, and perceived psychological costs of the AI can reduce this exchange.

Theoretical Contributions

This study makes four principal theoretical contributions. First, it builds on the social exchange theory (SET) to theorize technological preparedness and knowledge contribution as two successive forms of employee reciprocity in the context of AI-supported work. Simply put, traditional applications of SET typically account for how positive treatment of the organization leads to positive attitudes or behaviors of the employees. In the present findings a series of reciprocal responses may begin as an organizational investment, rather than a single behavioural response. Internal marketing is the investment in the organization, AI readiness is the readiness of the employee to act on that investment, AI-augmented knowledge sharing represents a subsequent contribution of knowledge resources, and finally productivity is the desired work-related outcome. This is a more dynamic implementation of SET to technologically changing workplaces. Second, the study adds to the growing body of literature on AI readiness, finding an organizational antecedent of employee readiness. Recent research has increasingly conceptualised AI readiness as an important capability for successful AI implementation (Wang et al., 2026). But readiness is often considered an employee or organizational state-of-being. This study theoretically positions readiness as being something that can be nurtured in an organization through investment in internal marketing, by establishing a positive relationship between the two. This study theoretically places readiness as something that can be produced by investing in an organization through internal marketing, as the study showed that there is a positive relationship between the two. This is a paradigm shift from whether employees are ready for AI to how organizational practices can make employees ready for AI. Internal marketing is thus not only relevant to employee-organization relationships, but also to the human aspect of technological change.

Third, the study contributes to the knowledge-sharing theory by conceptualizing the AI-augmented knowledge sharing as a mechanism connecting employee technological capability and productivity. The contribution is not to claim that AI-augmented knowledge sharing represents an entirely separate and established knowledge-sharing tradition. Rather, it extends established knowledge-sharing logic to an environment in which AI participates in the acquisition, processing and exchange of work-related knowledge. Existing AI research has shown that AI adoption can encourage knowledge sharing through learning opportunities (Hu et al., 2025), while human-AI collaboration research highlights the complementarity between human capabilities and technological capabilities. The present model integrates these ideas by positioning AI-augmented knowledge sharing after AI readiness and before productivity, thereby clarifying its role as an intermediate employee-level mechanism. Fourth, the study introduces AI anxiety as a boundary condition on the productivity value of AI-augmented knowledge sharing. Much of the emerging AI literature has focused on adoption, readiness, capability and performance benefits. However, employees may simultaneously experience uncertainty, job-related concerns and learning anxiety. By demonstrating that AI anxiety weakens the positive relationship between AI-augmented knowledge sharing and productivity, the study provides a more balanced theoretical account of AI-enabled work. The result supports the emerging view that AI can have simultaneously enabling and constraining consequences for employees (Chen et al., 2025; Tong et al., 2025). More importantly, the moderation finding enriches SET by suggesting that the exchange relationship is influenced not only by resources received from the organization but also by the perceived psychological costs associated with the technological environment.

Collectively, these contributions connect organizational investment, technological readiness, knowledge exchange and employee psychology within one theoretically integrated model. The study therefore moves beyond examining whether AI improves employee outcomes and instead explains how organizational practices enable AI-related productivity and under what psychological condition those benefits are weakened.

Practical Implications

The findings have several implications for banks operating in Pakistan, where AI adoption is developing alongside digital transformation and increasing demands for workforce reskilling. First, it is crucial for banks to consider AI readiness as a goal for their employees, not just IT. The roles of internal marketing and learning-

and-development should be merged into delivering role-specific AI training. Training should be provided to the various people in the organization who interact with the AI applications, in the context of the specific risks they may face, not in a generic AI workshop. Secondly, banks need to enhance internal communication regarding the implementation of AI. Staff need to be briefed on the tasks that will be supported by AI, tasks that can be automated, tasks that will need human judgment and new skills that will be necessary. This is significant given evidence from Pakistan suggests that employee anxiety over AI can negatively impact constructive response to AI adoption by the organization. So, managers should instead frame the adoption of AI as a reorganisation of the work and an enhancement of capabilities, not just as a technology replacement.

Third, Pakistani banks need to establish robust internal mechanisms for knowledge sharing with the help of AI. Employees might submit proven use cases, prompts, workflow enhancements, and frequently asked questions and verification steps to company knowledge bases. AI specific community of practice, with support across branches and functions, might help enable the sharing of AI learning. Recent studies have shown that AI can boost knowledge sharing when employees feel there are opportunities to learn and build their skills. Fourth, banks should not view AI anxiety as just an anti-technology stance but take proactive steps to tackle it. Guided practice and accessible support are recommended for employees with learning anxiety, and transparent reskilling and career-development options for employees who are concerned about losing their jobs. This is particularly important because recent evidence links AI anxiety with adverse employee outcomes and suggests that organizational knowledge-sharing can help employees cope with AI-related learning pressures. Finally, AI implementation should be accompanied by human-oversight and responsible-use protocols. Employees should know what customer information can be entered into AI systems, which AI-generated outputs require verification, and who remains accountable for AI-supported decisions. Banks should also evaluate productive AI use through indicators such as processing time, error reduction, service quality and knowledge-retrieval efficiency rather than simply measuring how frequently employees use AI.

Limitations and Future Directions

The study has several limitations that provide directions for future research. First, its cross-sectional design limits conclusions about the temporal ordering of the proposed relationships. Longitudinal or time-lagged research could examine whether changes in organizational support lead to subsequent changes in AI readiness, knowledge sharing and productivity, providing stronger evidence for the proposed sequential mechanism and responding to the need to examine AI-related employee outcomes over time (Savolainen et al., 2026). Second, the study relies on self-perceived productivity and self-reported measures. Although these capture employees' experiences of AI-enabled work, future research could combine employee responses with supervisor-rated performance and objective indicators such as processing time, error rates, customer-response time and actual AI-use metrics. Such multi-source designs could strengthen the empirical assessment of AI-related productivity outcomes. Third, the study focuses on Pakistan's banking sector, which may limit generalisability to other industries and national contexts. Future research could replicate the model across Pakistani industries and compare Pakistan with emerging and developed banking markets to examine whether institutional and technological differences alter the proposed relationships. Fourth, AI anxiety is explored as a single phenomenon. Future research could differentiate job-replacement anxiety, learning anxiety, and other types of AI-related anxiety, while exploring protective factors including AI self-efficacy, psychological safety, perceived organizational support, and trust in AI. This may explain the times at which employees are more likely to be able to use AI related resources in effective ways (Tong et al., 2025; Chen et al., 2025). Lastly, the overall process of AI-enabled knowledge sharing is explored. Research could separate out the various aspects of knowledge acquisition, creation, exchange and application with AI assistance. Such granularity can show where productivity gains and psychological expenses arise, especially when the AI-related knowledge and anxiety can impact employee learning (Liu et al., 2026).

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