



International Journal of Agriculture Extension and Social Development

ISSN Print: 2618-0723
ISSN Online: 2618-0731
NAAS Rating (2026): 5.04
IJAESD 2026; 9(9): 924-932
www.extensionjournal.com
Received: 08-06-2026
Accepted: 07-08-2026
Published: 25-09-2026

Shwetanshu S Dhoble

Department of Agricultural Economics, Dr. Sharadchandra Pawar College of MBA (Agri.), Baramati, Mahatma Phule Krishi Vidyapeeth, Rahuri, Dist. Ahilyanagar, Maharashtra, India

Understanding AI adoption in business: Benefits, barriers, and future adoption intention: An empirical study of Indian businesses

Shwetanshu S Dhoble¹

DOI: <https://www.doi.org/10.33545/26180723.2026.v9.i9.1.4297>

ABSTRACT

Purpose: This study examined the major applications, adoption maturity, continuance intention, and constraints associated with Artificial Intelligence (AI) use among businesses. It also assessed whether perceived benefit or organizational readiness more strongly predicts continuance intention.

Design/methodology/approach: A cross-sectional, descriptive-correlational survey was conducted among 100 business respondents evaluating or using AI. Data were collected using a structured 25-item questionnaire comprising Likert-scale, single-choice, and multi-select items. Frequency and percentage analysis, mean-score analysis, ranking, and Pearson's correlation coefficient were used.

Findings: AI was most widely applied in supply chain and logistics (40%), followed by sales forecasting and human resource management (36% each). Overall, 89% of businesses reported some level of AI engagement. Mean organizational readiness increased from 2.88 among non-adopters to 4.02 among fully adopted businesses. The continuance-intention mean was 3.83, with 75% likely or very likely to increase AI use within two to three years. Organizational readiness showed a stronger correlation with continuance intention ($r = 0.42$) than perceived benefit ($r = 0.31$). High implementation cost (25%), data privacy and security concerns (19%), and resistance to change (17%) were the leading constraints.

Research limitations/implications: The cross-sectional design and sample of 100 respondents may limit generalizability. The findings indicate a need for phased investment in infrastructure, skills, and governance to support sustained AI adoption.

Originality/value: The study provides empirical evidence of an attitude-capability gap and demonstrates that organizational readiness has a stronger association with continuance intention than perceived benefit, highlighting the importance of organizational capability in sustaining AI adoption.

Keywords: Artificial intelligence, AI adoption, Organizational readiness, Continuance intention, Technology adoption, Business

Introduction

Artificial Intelligence (AI) has emerged as one of the most transformative technologies of the twenty-first century, reshaping how business organizations plan, operate, and compete (Chen *et al.*, 2023) [1]. From automating repetitive processes to enabling predictive decision-making, AI is increasingly embedded into core business functions such as marketing, finance, human resource management, supply chain, and customer service. Organizations ranging from micro-enterprises to large multinationals are experimenting with AI-enabled tools to improve efficiency, reduce cost, and sustain competitive advantage, yet the pace and depth of this adoption vary considerably with organizational size, sector, financial capacity and, importantly, the underlying readiness of the organization to absorb technological change (Jöhnk *et al.*, 2021; Schwaeke *et al.*, 2024) [2, 3].

The Technology Acceptance Model (TAM) proposed by Davis (1989) [4] explains that perceived usefulness and perceived ease of use drive the acceptance of information technology, while Rogers (2003) [5], through the Diffusion of Innovations framework, argues that relative advantage, compatibility, complexity, trialability and observability jointly determine the speed of adoption. The Technology-Organization-Environment (TOE) framework of Tornatzky *et al.* (1990) [6] extends this view by emphasizing that adoption outcomes depend jointly on technological characteristics, organizational readiness, and environmental conditions; a recent meta-analysis of twelve empirical studies spanning 3,398 respondents confirms that seven of the eight TOE factors exert a statistically significant effect on organizational AI adoption across industries (Pinto *et al.*, 2025) [7]. For continued or sustained use, Bhattacharjee's (2001) [8] Expectation-Confirmation Model (ECM) further proposes that post-adoption continuance is governed less by initial attitude than by confirmed expectations and structural capability, a mechanism recently re-confirmed in AI-specific continuance contexts where confirmation, perceived usefulness and satisfaction jointly predict sustained use (Guo *et al.*, 2026) [9]. Taken together, these frameworks suggest that a favourable attitude toward AI is necessary but not sufficient: organizations must

Corresponding Author:

Shwetanshu S Dhoble

Department of Agricultural Economics, Dr. Sharadchandra Pawar College of MBA (Agri.), Baramati, Mahatma Phule Krishi Vidyapeeth, Rahuri, Dist. Ahilyanagar, Maharashtra, India

also build the infrastructure, skills, culture and policy required to sustain AI use, a distinction Gallivan (2001) [10] captures as the difference between the decision to adopt a technology and its subsequent assimilation into routine practice.

Empirical work supports this view across business functions. Chen *et al.* (2023) [1] linked firm-level AI adoption intensity to improved marketing performance; Smith *et al.* (2024) [11] found AI particularly suited to structured, data-intensive finance tasks, a conclusion reinforced by Roos *et al.* (2025) [12], who identify suitable IT infrastructure, high-quality data, regulatory compliance and workforce upskilling as prerequisites for AI adoption in accounting functions such as invoice processing, anomaly detection and financial forecasting; Agarwal (2022) [13] reported expected gains in recruitment efficiency from AI use in human resource management; and Dora *et al.* (2022) [14] and Hangl *et al.* (2022) [15] identified organizational, technical and social factors shaping AI adoption in supply chains. At the organizational level, Jöhnk *et al.* (2021) [2] demonstrated that a positive attitude toward AI does not by itself guarantee readiness, and Dreyling *et al.* (2024) [16] proposed that AI adoption unfolds through discrete maturity stages requiring corresponding investment in infrastructure and governance. This staged conceptualization is echoed by Kallemparambil *et al.* (2025) [17], who developed a tailored organizational-readiness model specifically for resource-constrained firms, arguing that AI readiness must be assessed and built dimension-by-dimension rather than treated as a single attitudinal threshold. Li *et al.* (2024) [18] linked technological readiness to willingness to use AI, while Binsaeed *et al.* (2023) [19] identified knowledge-sharing as an important enabler of adoption, and Lee *et al.* (2023) [20] confirmed that AI implementation affects organizational, technological and people-related dimensions simultaneously. Extending the TOE lens to small and medium enterprises specifically, Sánchez *et al.* (2025) [21] integrate TOE with Diffusion of Innovations constructs to show that compatibility, complexity tolerance, and data competence jointly determine whether SMEs progress beyond early experimentation, while ul Haq *et al.* (2025) [22] demonstrate, in a Pakistani manufacturing sample, that AI adoption mediates the effect of technological readiness and leadership vision on firm performance. A recent bibliometric and systematic review of the SME AI-adoption literature by Yesuf *et al.* (2025) [23] similarly converges on three dominant thematic clusters, AI-driven innovation, entrepreneurial decision-making, and adoption barriers/enablers centred on organizational readiness, digital infrastructure, human capital and financial capability that closely mirror the constructs examined in the present study.

Despite these benefits, AI adoption continues to be constrained by well-documented barriers. The OECD (2025) [24] and Gartner (2019) [25] identify cost, skill shortages, and difficulty finding appropriate use cases as recurring obstacles, particularly for small and medium enterprises; AICPA *et al.* (2026) [26] report persistent gaps in AI-skilled talent and governance preparedness between early adopters and laggards; and, in the Indian context specifically, The Dialogue (2026) [27] identifies data-privacy concerns, limited technical expertise, and integration difficulties as significant barriers. A large-scale systematic review of 106 peer-reviewed studies similarly finds that compatibility, infrastructure, knowledge, resources, culture, competition, regulation and ecosystem support constitute recurring TOE-based clusters of enablers and inhibitors across the SME literature (Schwaeye *et al.*, 2024) [3]. Focusing specifically on Indian micro, small and medium enterprises, Ganguly *et al.* (2025) [28] apply the Best-Worst Method to rank and interlink adoption barriers, finding that lack of top-management support and resistance to change function as organizational bottlenecks that, in turn, amplify technology- and environment-related barriers a pattern of interacting, rather than isolated, constraints that is highly consistent with the structural gap examined in the present study. Resistance to organizational change further compounds these constraints, though Li *et al.* (2023) [29] suggest its negative effects can be mitigated through leadership and high-performance work systems. In agriculture-adjacent sectors, Mishra *et al.* (2023) [30] similarly found implementation cost, infrastructure

shortage and lack of standardization to be leading challenges, while Hirtranusi *et al.* (2026) [31] confirm, through a systematic review grounded in the TOE framework, that organizational readiness for AI is inherently multidimensional.

India is undergoing rapid digital transformation, supported by improving infrastructure and growing AI literacy, yet there remains limited primary survey evidence that jointly examines, within a single Indian business sample, the ranked applications of AI, the distribution of businesses across adoption stages, the empirically measured magnitude of future intention, and the ranked barriers to adoption. Most recent contributions either analyse SMEs qualitatively across multiple countries (Schwaeye *et al.*, 2024; Sánchez *et al.*, 2025) [3, 21], model firm performance rather than continuance intention (ul Haq *et al.*, 2025) [22], or focus narrowly on barrier ranking without linking barriers to a measured attitude-capability gap (Ganguly *et al.*, 2025) [28]. None of these studies simultaneously quantifies the numerical gap between perceived benefit and organizational readiness and tests which construct more strongly predicts continuance intention within the same sample the specific empirical contribution this study offers. Building on this gap, the present study was designed with four specific objectives: (i) to study the major applications of AI used by businesses; (ii) to examine the level of AI adoption among businesses; (iii) to study the future (continuance) intention of businesses to use AI, including whether perceived benefit or organizational readiness more strongly predicts this intention; and (iv) to study the constraints of using AI in business.

Materials and Methods

1. Research design and approach

This study used a cross-sectional, quantitative survey design with both descriptive and correlational analysis. The descriptive analysis covered the applications of AI, the level of AI adoption, and the constraints to AI use through frequency and percentage analysis. The correlational analysis examined the relationship between perceived benefit, organizational readiness, and continuance intention through mean-score/ranking analysis supported by Pearson's correlation analysis. The overall design draws on the Technology-Organization-Environment framework (Tornatzky *et al.*, 1990) [6] and the Expectation-Confirmation Model (Bhattacharjee, 2001) [8] as guiding theoretical lenses, consistent with recent TOE-based empirical designs used to study AI adoption in SME and business-survey contexts (Pinto *et al.*, 2025; Sánchez *et al.*, 2025; ul Haq *et al.*, 2025) [7, 21, 22].

2. Population, sampling and sample size

The study population included businesses that were evaluating or already using AI, ranging from businesses with no adoption to those with organization-wide adoption. Data were collected through a structured questionnaire survey administered to 100 business respondents ($n = 100$), with responses anonymized and recorded using a respondent identifier (R001–R100).

3. Data collection

Primary data were collected using a structured, self-administered questionnaire covering respondents' views of AI benefits, organizational readiness, adoption level, future intention, and constraints to adoption. Data were collected in Pune City, Maharashtra, between 17 April 2026 and 16 May 2026. Secondary data were drawn from peer-reviewed journal articles and institutional survey reports (OECD, Gartner, AICPA and CIMA) relating to AI adoption in business, as detailed in the literature reviewed above.

4. Instrument and measurement scale

The questionnaire contained 25 items, including 5-point Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree), single-choice items, and multi-select items. Attitudinal and perception-based items were measured on the 5-point Likert scale, while single-choice and multi-select items used nominal/ordinal categories appropriate to each question (e.g., AI adoption stage, biggest barrier to adoption, likely

hood of increasing AI use). The item structure was informed by constructs used in recent TOE- and ECM-based AI-adoption instruments (Bhattacharjee, 2001; Tornatzky *et al.*, 1990; Pinto *et al.*, 2025) [8, 6, 7], adapted to the applications, adoption-stage, and barrier categories most frequently reported in the Indian and international SME literature (Ganguly *et al.*, 2025; Sánchez *et al.*, 2025) [28, 21].

5. Constructs of the study

Three main constructs were used for the correlation analysis. Perceived Benefit was computed as the mean of four items covering efficiency, decision-making speed, productivity, and overall business efficiency. Organizational Readiness was computed as the mean of six items covering infrastructure, employee skills, overall preparedness, organizational culture, policies/processes, and employee willingness to learn. Continuance Intention, the dependent construct, was computed as the mean of two items measuring intention to continue using AI and likelihood of recommending AI to other businesses.

6. Statistical analysis

Data on the major applications of AI used by businesses, the level of AI adoption among businesses, and the constraints of using AI in business were analysed using frequency and percentage analysis. For the future (continuance) intention of businesses to use AI, mean scores were computed for the Continuance Intention items and ranked, and construct-level means and standard deviations were computed for Perceived Benefit, Organizational Readiness, and Continuance Intention. Pearson's product-moment correlation coefficient (r) was computed to examine the strength and direction of association between Perceived Benefit, Organizational Readiness, and Continuance Intention, and the resulting matrix is additionally visualised as a correlation heat-map (Figure 6) to aid interpretation. Mean Organizational Readiness was further cross-tabulated

against AI adoption stage to examine whether readiness varies systematically with adoption maturity. Correlations are reported as descriptive associations consistent with the cross-sectional design and do not imply causation, in line with recent TOE-based survey studies that similarly report correlational rather than causal evidence (Pinto *et al.*, 2025; ul Haq *et al.*, 2025) [7, 22]. All descriptive and correlational computations were performed using standard spreadsheet and statistical software, and all figures reported were cross-verified against the underlying respondent-level survey dataset ($n = 100$) prior to reporting.

Results

1. Major applications of AI used by businesses

Table 1 presents the major functional areas in which AI is applied by the surveyed businesses, based on a multi-select item; consequently, percentages do not sum to 100. Supply chain and logistics was the most widely reported application (40%), followed closely by sales forecasting and human resource management (36% each). Finance and accounting and production/operations were each reported by 30% of respondents, followed by data analysis and decision-making (27%), customer service (25%), and marketing and advertising (23%), which ranked last.

The concentration of AI use in supply chain and logistics, sales forecasting, and human resource management indicates that businesses currently perceive the greatest value from AI in operational and managerial functions rather than customer-facing functions such as marketing and customer service. This pattern aligns with Dora *et al.* (2022) [14], who identified organizational readiness and management support as critical success factors in food-supply-chain AI adoption, and with Agarwal (2022) [13], who linked HR-focused AI adoption to expected gains in recruitment efficiency.

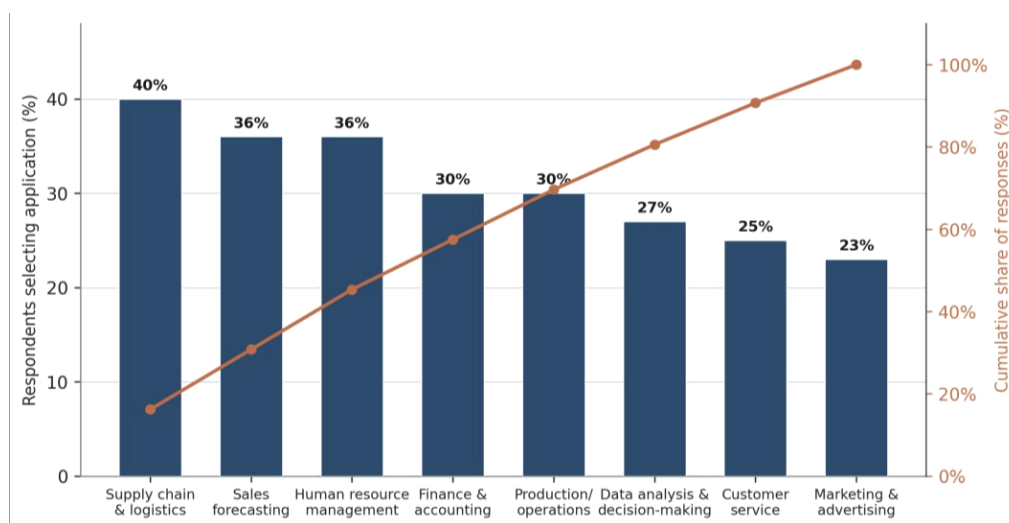


Figure 1. Major applications of AI used by businesses (Pareto analysis, $n = 100$)

2. Level of AI adoption among businesses

Table 2 shows that partial adoption in some functions was the most common adoption stage (27%), followed by exploring/evaluating (22%). Full adoption across the organization and pilot projects were

each reported by 20% of businesses, while 11% reported no adoption. In total, 89% of businesses reported some level of AI engagement.

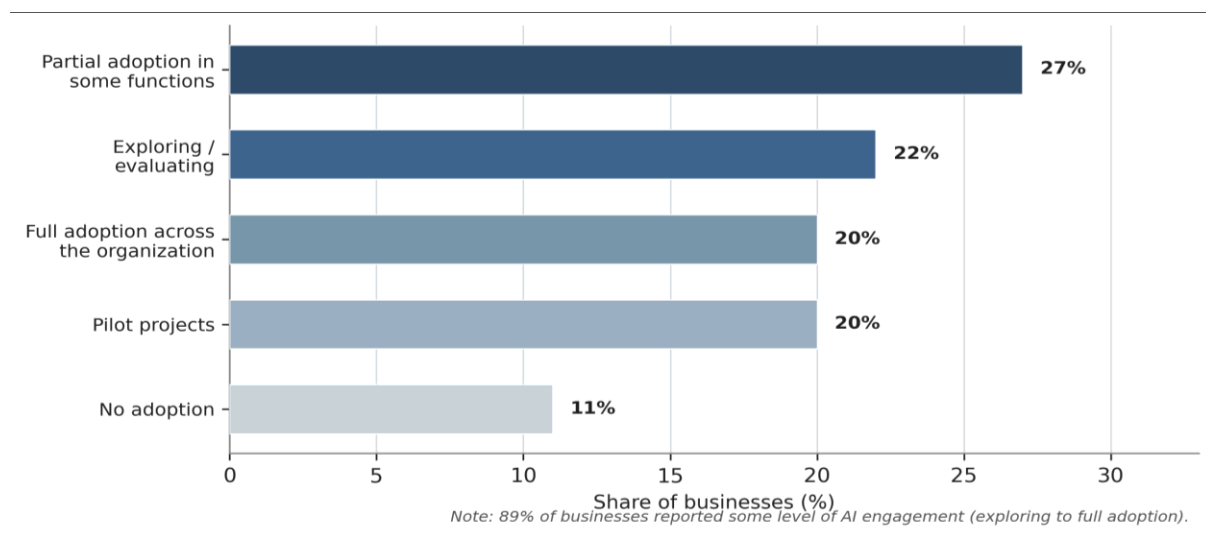
Table 1. Major Applications of AI Used by Businesses ($n = 100$)

Rank	Application Area	Frequency	% of Respondents
I	Supply chain and logistics	40	40
II	Sales forecasting	36	36
II	Human resource management	36	36
IV	Finance and accounting	30	30
IV	Production/operations	30	30
VI	Data analysis and decision-making	27	27
VII	Customer service	25	25
VIII	Marketing and advertising	23	23

Source: AI Adoption Survey dataset (multi-select item); $n = 100$. Percentages do not sum to 100 as multiple responses were permitted.

Table 2. Level of AI Adoption among Businesses ($n = 100$)

Rank	AI Adoption Level	Frequency	%
I	Partial adoption in some functions	27	27
II	Exploring / evaluating	22	22
III	Full adoption across the organization	20	20
III	Pilot projects	20	20

**Figure 2.** Level of AI adoption among business ($n = 100$)

To understand adoption maturity more clearly, mean Organizational Readiness was cross-tabulated against adoption stage (Table 3). Readiness rose monotonically from 2.88 (no adoption) to 2.91 (exploring/evaluating), 3.33 (pilot projects), 3.93 (partial adoption), and 4.02 (full adoption). This pattern is consistent with the TOE

framework (Tornatzky *et al.*, 1990) [6] and with Dreyling *et al.* (2024) [16], and suggests that deeper organizational readiness accompanies, and is likely necessary for, advancement to more mature adoption stages rather than adoption maturity being driven by attitude alone.

IV	No adoption	11	11
—	Total	100	100

Source: AI Adoption Survey dataset (single-choice item); $n = 100$.

Table 3. Mean Organizational Readiness across AI Adoption Stages ($n = 100$)

AI Adoption Level	n	Mean Organizational Readiness (1–5)
No adoption	11	2.88
Exploring / evaluating	22	2.91
Pilot projects	20	3.33
Partial adoption in some functions	27	3.93
Full adoption across the organization	20	4.02

Source: AI Adoption Survey dataset, cross-tabulation of adoption stage against Organizational Readiness Mean; $n = 100$.

(continued on next page)

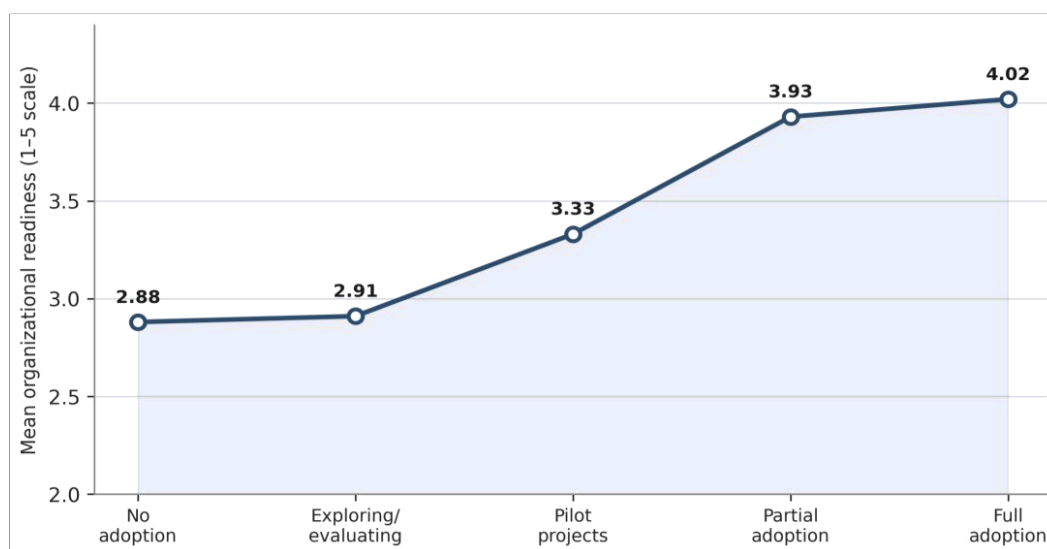


Figure 3. Mean organizational readiness across AI adoption stages ($n = 100$)

3. Future (continuance) intention to use AI

Continuance Intention was measured through two items: intention to continue using AI, and likelihood of recommending AI to other businesses. The recommend-AI item (mean = 4.01) ranked ahead of the continue-using item (mean = 3.64), yielding an overall Continuance Intention mean of 3.83 (an intention index of 76.6%). Table 4 compares the three key constructs: mean Continuance Intention (3.83) exceeded mean Perceived Benefit (3.74), which in turn exceeded mean Organizational Readiness (3.49) a 0.25-point gap between Perceived Benefit and Organizational Readiness that constitutes direct empirical evidence of the attitude-capability gap motivating this study.

Continuance Intention 3.83 0.76 Positive

Table 4. Construct mean comparison perceived benefit, organizational readiness, and continuance intention ($n = 100$)

Construct	Mean (1–5)	SD	Interpretation
Perceived Benefit	3.74	0.55	Positive
Organizational Readiness	3.49	0.76	Moderate-positive

Source: AI Adoption Survey dataset; $n = 100$.

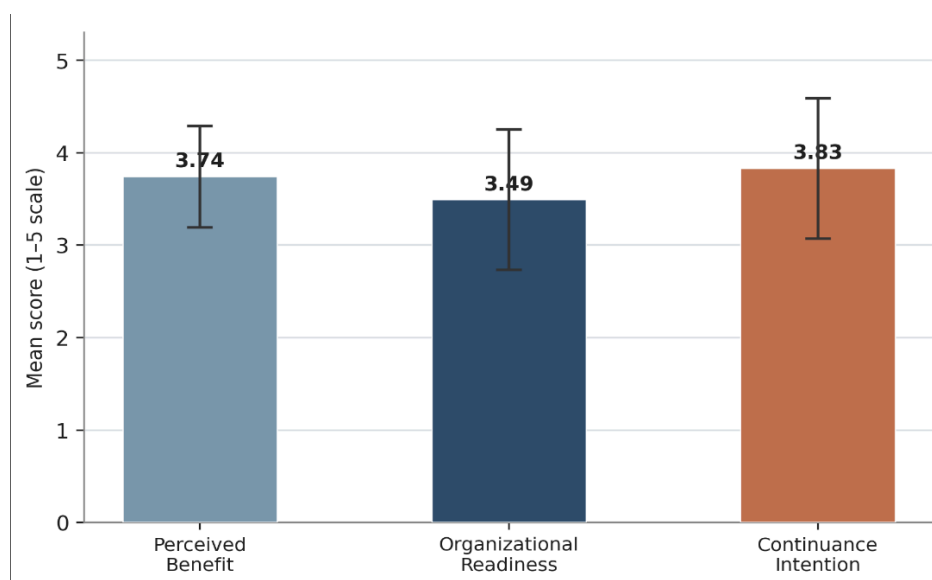


Figure 4. Comparison of mean construct scores ($\pm$ SD)

Table 5 shows that Organizational Readiness correlated more strongly with Continuance Intention ($r = 0.42$, moderate positive) than did Perceived Benefit ($r = 0.31$, weak-to-moderate positive), while Perceived Benefit and Organizational Readiness were themselves positively correlated ($r = 0.61$). This finding is consistent with Bhattacharjee's (2001) [8] Expectation-Confirmation Model and with

Jöhnk *et al.* (2021) [2], both of which indicate that post-adoption continuance is driven more by structural, confirmed capability than by initial attitude. In addition, 75% of respondents indicated they were likely or very likely to increase AI use in the next two to three years, while only 12% considered this unlikely.

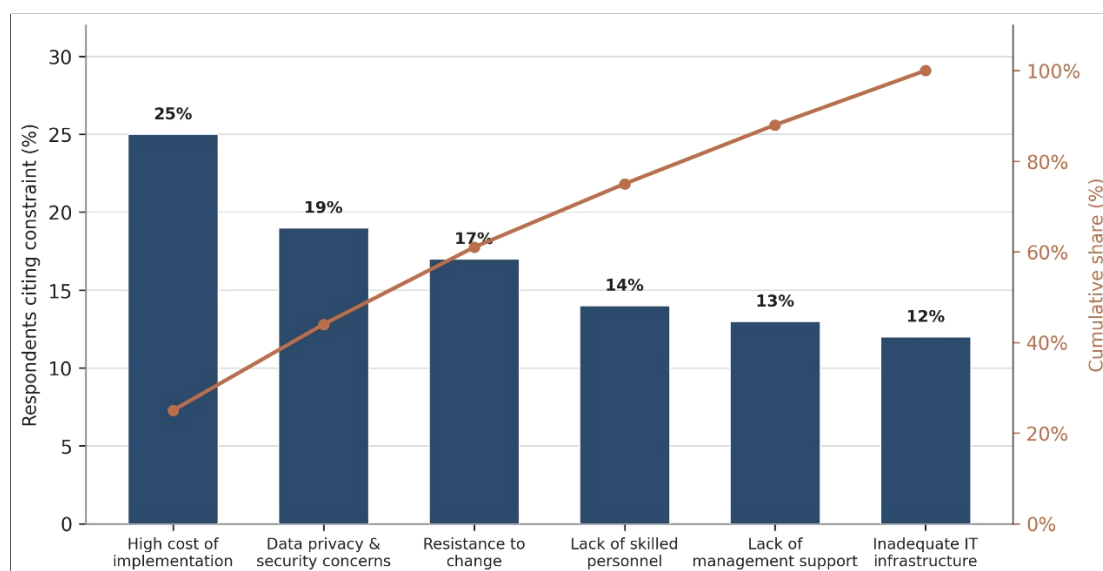


Figure 5. Major constraints to AI adoption in business (Pareto analysis, $n = 100$)

4. Constraints of using AI in business

High cost of implementation was the leading constraint, reported as the single biggest barrier by 25% of businesses (Table 6). Data privacy and security concerns ranked second (19%), followed by resistance to change (17%), lack of skilled personnel (14%), lack of management support (13%), and inadequate IT infrastructure (12%).

Notably, concern about data privacy and security was far more pervasive than its 19% ranking suggests: 55% of all respondents reported being very or extremely concerned about data privacy and security, indicating that this concern cuts across the sample rather than being confined to a minority, and persists even among businesses at higher levels of adoption.

Table 5. Pearson correlation matrix among perceived benefit, organizational readiness, and continuance intention

Relationship	Pearson r	Interpretation
Organizational Readiness ↔ Continuance Intention	0.42	Moderate positive
Perceived Benefit ↔ Continuance Intention	0.31	Weak–moderate positive
Perceived Benefit ↔ Organizational Readiness	0.61	Positive

Source: AI Adoption Survey dataset; $n = 100$. Correlations are descriptive associations and do not establish causation, consistent with the cross-sectional design.

These findings align with the OECD (2025) [24] and Gartner (2019) [25], both of which identify cost and skill-related barriers as leading obstacles to enterprise AI adoption, and with The Dialogue (2026) [27], which similarly found data-privacy and security concerns to be a leading barrier among Indian businesses. The third-ranked position of resistance to change is consistent with Li *et al.* (2023) [29], who identified employee resistance as a distinct barrier mitigable through lead-

ership and work-system interventions. Using an independently collected sample of Indian MSMEs and the Best-Worst Method rather than simple frequency ranking, Ganguly *et al.* (2025) [28] similarly place cost- and management-related barriers ahead of purely technological ones and, importantly, show that these barriers are interlinked rather than independent a structural insight that helps explain

Table 6. Constraints/Barriers to AI Adoption in Business ($n = 100$)

Rank	Constraint	Frequency	%
I	High cost of implementation	25	25
II	Data privacy and security concerns	19	19
III	Resistance to change	17	17
IV	Lack of skilled personnel	14	14
V	Lack of management support	13	13
VI	Inadequate IT infrastructure	12	12
—	Total	100	100

Source: AI Adoption Survey dataset (single-choice, biggest barrier); $n = 100$.

why, in the dataset used in this study, data-privacy concern remains widespread (55%) even though it was named the single biggest barrier by only 19% of respondents: it appears to function as a background constraint that compounds the effect of other, more visibly

ranked barriers rather than acting in isolation. The association between adoption barriers and adoption stage was examined but was not found to be statistically significant in the underlying dataset and is therefore reported descriptively.

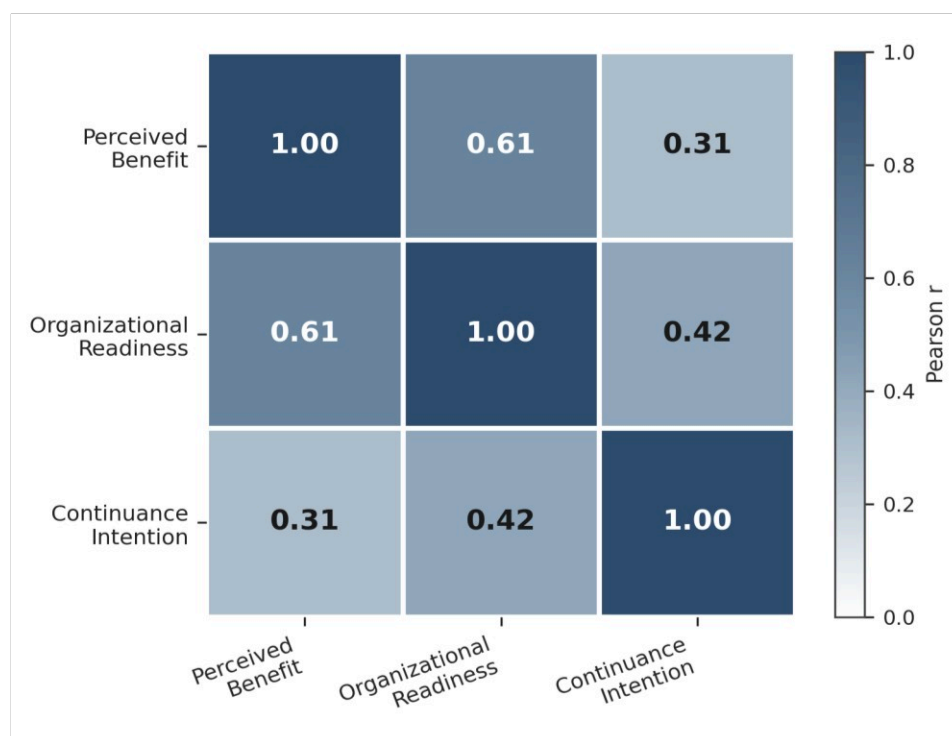


Figure 6. Correlation matrix: perceived benefit, organizational readiness and continuance intention

Discussion

The results indicate that businesses are attitudinally ready for AI but remain organizationally behind the central attitude-capability gap this study set out to examine. Businesses reported high perceived benefit (3.74) and high continuance intention (3.83), yet organizational readiness (3.49) lagged both, and it was organizational readiness rather than perceived benefit that more strongly predicted continuance intention ($r = 0.42$ versus $r = 0.31$). This pattern is consistent with the Expectation-Confirmation Model (Bhattacharjee, 2001) [8], which holds that sustained use is governed by confirmed, structural capability rather than initial enthusiasm, and with the TOE framework (Tornatzky *et al.*, 1990) [6], which frames adoption outcomes as jointly determined by technological, organizational and environmental conditions. It also corroborates Jöhnk *et al.* (2021) [2], who found that a favourable attitude toward AI does not, by itself, guarantee organizational readiness, and Dreyling *et al.* (2024) [16], whose maturity-stage conceptualization is directly reflected in the monotonic rise of readiness scores from 2.88 at no-adoption to 4.02 at full adoption observed here. The magnitude of the readiness–continuance association ($r = 0.42$) is also broadly consistent with Guo *et al.*'s (2026) [9] recent structural-equation evidence that confirmation and perceived usefulness proxies for realised, rather than merely anticipated, capability are stronger predictors of AI continuance intention than initial attitude, reinforcing the view that the dataset used in this study's 0.25-point benefit–readiness gap is a meaningful early-warning indicator rather than a statistical artefact.

The concentration of AI applications in supply chain and logistics, sales forecasting, and human resource management suggests that businesses currently derive the greatest perceived value from AI in operational and managerial functions rather than customer-facing activities. This is consistent with Dora *et al.* (2022) [14] and Hangl *et al.* (2022) [15] on supply-chain AI adoption, and with Agarwal (2022) [13] on HR-focused adoption, and may reflect the relatively structured, data-intensive

nature of these functions, echoing Smith and Ayele's (2024) [11] observation that AI is best suited to structured tasks while human judgment remains important elsewhere. The comparatively lower ranking of marketing and customer service is noteworthy given field-experimental evidence that generative AI conversational assistants can raise customer-support agent productivity substantially, particularly for

less-experienced staff (Brynjolfsson *et al.*, 2025) [32]; this divergence suggests that the productivity gains documented in large, technologically mature firms have not yet been widely realised or perceived by the smaller and mid-sized businesses in the sample used in this study, consistent with Ortal and Magpantay's (2025) [33] finding that generative AI chatbot adoption in customer support depends on service-quality and service-satisfaction determinants that resource-constrained organizations may not yet have in place. This functional concentration also mirrors Sánchez *et al.*'s (2025) [21] observation that SMEs internationally tend to favour simpler, off-the-shelf AI solutions targeted at operational efficiency and customer-service automation over more strategically ambiguous, judgment-intensive functions, suggesting that the pattern observed in the Indian sample examined in this study reflects a broader, cross-national tendency rather than a sector-specific idiosyncrasy.

The persistence of high implementation cost, data-privacy concern, and resistance to change as leading constraints regardless of adoption maturity supports the view, advanced by the OECD (2025) [24], Gartner (2019) [25], and The Dialogue (2026) [27], that these barriers are structural rather than transitional. The finding that 55% of respondents reported high data-privacy concern, considerably exceeding its 19% ranking as the single biggest barrier, indicates that privacy concern operates as a pervasive undercurrent across the sample rather than a decisive constraint for only a subset of businesses. This aligns with Mishra *et al.* (2023) [30], who similarly identified cost and infrastructure shortages as dominant, cross-cutting barriers in an Indian agri-business context, and reinforces Hirtranusi *et al.*'s (2026) [31] conclusion that organizational readiness for AI is inherently multidimensional, requiring alignment across infrastructure, competencies, and governance rather than resolution through any single intervention. Most directly, the barrier ranking obtained here cost, followed by privacy/security, followed by resistance to change closely parallels the interlinked barrier structure reported by Ganguly *et al.* (2025) [28] among Indian MSMEs, who found using the Best-Worst Method that lack of top-management support and change resistance function as upstream organizational bottlenecks that intensify downstream technological and environmental barriers; this convergence across two independently collected Indian business samples strengthens confidence that the barrier hierarchy identified in the present study is a genuine, generalizable feature of the Indian business environment rather than a sampling artefact. It is also consistent with the broader

cross-country evidence assembled by Schwaeke *et al.* (2024) [3], whose systematic review of 106 studies similarly clusters cost, infrastructure, knowledge and cultural resistance as recurring TOE-based barrier categories across SME contexts worldwide.

Overall, the findings suggest that AI adoption strategy should shift emphasis from cultivating positive attitudes which, at 3.74, are already comparatively strong toward deliberately closing the 0.25-point organizational-readiness gap through investment in infrastructure, staff training, data governance, and change management, consistent with Li *et al.*'s (2023) [29] finding that leadership and work-system interventions can mitigate resistance to change. This recommendation aligns with Kalleparambil and Akoum's (2025) [17] tailored readiness model, which argues that resource-constrained firms should assess and build readiness dimension-by-dimension (technological, organizational, and data-governance readiness) rather than treating a single favourable attitude score as evidence of preparedness, and with ul Haq *et al.*'s (2025) [22] finding that AI adoption's effect on firm performance operates through, rather than around, organizational readiness and leadership vision. Practically, businesses beginning or scaling their AI journey may benefit from sequencing adoption toward functions where AI currently delivers demonstrable value (supply chain, sales forecasting, HR) to build organizational momentum before extending AI into functions where perceived value and readiness are comparatively lower.

1. Theoretical and practical implications

Theoretically, this study contributes to the technology-adoption literature by empirically testing, within a single Indian business sample, the relative predictive strength of perceived benefit versus organizational readiness a comparison that recent TOE-based studies (Pinto *et al.*, 2025; Sánchez *et al.*, 2025; ul Haq *et al.*, 2025) [7, 21, 22] have examined mainly through adoption or performance outcomes rather than through continuance intention specifically. By explicitly quantifying the gap between perceived benefit and organizational readiness (0.25 points) and linking it to differential correlation strength with continuance intention, the study offers a replicable, low-cost diagnostic that future TOE- and ECM-based studies could adopt to benchmark the attitude-capability gap across other sectors and regions. Practically, the findings imply that business managers and policymakers should treat AI adoption strategy as a readiness-building exercise rather than a technology-procurement exercise: phased-cost pilots and transparent data-governance policies directly target the two leading constraints identified here, structured change-management programmes address the third-ranked constraint (resistance to change), and sequencing adoption toward already high-value functions (supply chain, sales forecasting, HR) builds the organizational momentum that Dreyling *et al.* (2024) [16] and Kalleparambil *et al.* (2025) [17] identify as a precondition for progressing to full, organization-wide adoption.

2. Limitations

The findings should be considered in light of several limitations. First, the study relies on self-reported perceptions collected through a structured questionnaire rather than independently verified adoption behaviour, which may introduce social-desirability bias, particularly for organizational-readiness and continuance-intention items. Second, the sample of 100 respondents, drawn from a single survey instrument administered in one city, may not generalize across industries, firm sizes, or regions; larger, multi-region samples of the kind assembled by Schwaeke *et al.* (2024) [3] and ul Haq *et al.* (2025) [22] would strengthen external validity. Third, the cross-sectional design captures perceptions at a single point in time and can establish association but not causal direction between organizational readiness and continuance intention, a limitation shared by most TOE-based survey studies in this literature (Pinto *et al.*, 2025) [7] and one that longitudinal designs are better positioned to resolve. Finally, the association between adoption barriers and adoption stage was examined but was not found to be statistically significant in the underlying dataset and should there-

fore be interpreted with caution rather than generalized to other business contexts.

Conclusion

This study examined the applications, adoption maturity, continuance intention, and constraints associated with AI use among 100 Indian businesses currently evaluating or using AI. AI adoption was found to be concentrated in operational and managerial functions, particularly supply chain and logistics, sales forecasting, and human resource management, a pattern consistent with international SME evidence (Sánchez *et al.*, 2025; Schwaeke *et al.*, 2024) [21, 3]. Although 89% of businesses reported some level of AI engagement and continuance intention was generally high (76.6%), organizational readiness consistently lagged behind perceived benefit, and it was organizational readiness not perceived benefit alone that more strongly predicted businesses' intention to continue using AI, corroborating recent TOE- and ECM-based evidence (Pinto *et al.*, 2025; Guo *et al.*, 2026) [7, 9]. High implementation cost, data-privacy and security concerns, and resistance to change emerged as persistent, structural constraints that do not appear to resolve with adoption experience alone, and their ranking and interlinkage closely mirror independent evidence from Indian MSMEs (Ganguly *et al.*, 2025) [28]. These findings confirm a measurable attitude-capability gap and suggest that sustained AI adoption depends less on cultivating enthusiasm than on the deliberate, phased building of organizational infrastructure, skills, and governance, consistent with tailored readiness models proposed for resource-constrained firms (Kalleparambil *et al.*, 2025; ul Haq *et al.*, 2025) [17, 22]. Future research employing larger, multi-region, multi-instrument and longitudinal designs is needed to establish whether these relationships generalize across industries and to test the causal direction between organizational readiness and continuance intention.

References

1. Chen J, Zhou W, Frankwick GL. Firm AI adoption intensity and marketing performance. *Journal of Computer Information Systems*. 2023;65(2).
2. Jöhnk J, Weißert M, Wyrski K. Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business and Information Systems Engineering*. 2021;63(1):5-20.
3. Schwaeke J, Peters A, Kanbach DK, Kraus S, Jones P. The new normal: The status quo of AI adoption in SMEs. *Journal of Small Business Management*. 2024;63(3):1297-1331.
4. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*. 1989;13(3):319-340.
5. Rogers EM. *Diffusion of innovations*. 5th ed. Free Press; 2003.
6. Tornatzky LG, Fleischer M. *The processes of technological innovation*. Lexington Books; 1990.
7. Pinto AS, Abreu A, Pérez Cota M. A meta-analysis of TOE factors driving organizational adoption of artificial intelligence across industries. *Discover Artificial Intelligence*. 2025.
8. Bhattacharjee A. Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*. 2001;25(3):351-370.
9. Guo Z, Liang Y, Liu Y. Determinants of college students' continuance intention toward generative AI teammates: An integrated Expectation-Confirmation and Shared Mental Model approach. *Algorithms and Architectures for Parallel Processing (ICA3PP 2025)*, Lecture Notes in Computer Science. 2026;16388.
10. Gallivan MJ. Organizational adoption and assimilation of complex technological innovations. *ACM SIGMIS Database*. 2001;32(3):51-85.
11. Smith G, Ayele WY. Assessing the suitability of artificial intelligence to accomplish organizational finance tasks. *Lecture Notes in Computer Science*. 2024.

12. Roos D, Schlegel D, Kraus P. Adopting artificial intelligence in accounting: Prerequisites and applications. *Journal of Electronic Business and Digital Economics*. 2025;4(2):374-384.
13. Agarwal A. AI adoption by human resource management: A study of its antecedents and impact on HR system effectiveness. *Foresight*. 2022;25(1).
14. Dora M, Kumar A, Mangla SK, Pant A, Kamal MM. Critical success factors influencing artificial intelligence adoption in food supply chains. *International Journal of Production Research*. 2022;60(14):4621-4640.
15. Hangl J, Behrens VJ, Krause S. Barriers, drivers, and social considerations for AI adoption in supply chain management: A tertiary study. *Logistics*. 2022;6(3):63.
16. Dreyling R, Lemmik J, Tammet T, Pappel I. An artificial intelligence maturity model for the public sector: A design science approach. 2024.
17. Kalleparambil SA, Akoum M. AI organisational readiness for SMEs: A tailored model for AI adoption success. *Journal of Information and Knowledge Management*. 2025;24(6).
18. Li H, Ren T, Zhang Z. Assistive tools or insecurity: The impact of technological readiness on willingness to use AI. *International Journal of Human-Computer Interaction*. 2024.
19. Binsaeed RH, Yousaf Z, Grigorescu A, Samoila A, Chitescu RI, Nassani AA. Knowledge sharing key issue for digital technology and artificial intelligence adoption. *Systems*. 2023;11(7):316.
20. Lee MCM, Scheepers H, Lui AKH, Ngai EWT. The implementation of artificial intelligence in organizations: A systematic literature review. *International Journal of Information Management*. 2023.
21. Sánchez E, Calderón R, Herrera F. Artificial intelligence adoption in SMEs: Survey based on TOE–DOI framework, primary methodology and challenges. *Applied Sciences*. 2025;15(12):6465.
22. ul Haq F, Suki NM, Zaigham H, Masood A, Rajput A. Exploring AI adoption and SME performance in resource-constrained environments: A TOE–RBV perspective with mediation and moderation effects. *Journal of Digital Economy*. 2025;doi: 10.1016/j.jdec.2025.07.002.
23. Yesuf Y, Fields Z, Jain A, Kassa E. Artificial intelligence adoption as a driver of innovation and competitiveness in SMEs: A bibliometric and systematic review. *F1000Research*. 2025;doi: 10.12688/f1000research.171494.1.
24. OECD. AI adoption by small and medium-sized enterprises. OECD Publishing; 2025.
25. Gartner. CIO agenda survey: 3 barriers to AI adoption. Gartner Inc. 2019.
26. AICPA and CIMA. Global survey reveals growing AI adoption gap as organizations struggle with talent, technology, and governance readiness. 2026.
27. The Dialogue. Competition, innovation, and market structure in India's AI ecosystem: An empirical assessment. 2026.
28. Ganguly B, Roy Chowdhury S, Ghosh R, Ghosh D. What hinders AI adoption in MSMEs of India? – Importance and interlinkages between the barriers. *Indian Growth and Development Review*. 2025;18(1):72-92.
29. Li C, Ashraf SF, Amin S, Safdar MN. Consequence of resistance to change on AI readiness. *SAGE Open*. 2023.
30. Mishra D, Muduli K, Raut R, Kumar A *et al*. Challenges facing artificial intelligence adoption during COVID-19 pandemic: An investigation into the agriculture and agri-food supply chain in India. *Sustainability*. 2023;15(8):6377.
31. Hirtranusi SA, Ranti B, Nugroho WS, Jatmiko W. A systematic literature review on organizational readiness for artificial intelligence adoption based on the TOE framework. *International Journal of Advanced Computer Science and Applications*. 2026;17(1):491-503.
32. Brynjolfsson E, Li D, Raymond LR. Generative AI at work. *The Quarterly Journal of Economics*. 2025;140(2):889-942.
33. Ortal JC, Magpantay LAK. Determinants of generative AI-based chatbot adoption in customer support. In: Patel KK, Santosh K, Gomes de Oliveira G, Patel A, Ghosh A, editors. *Soft Computing and Its Engineering Applications (icSoftComp 2024)*. Communications in Computer and Information Science. Springer; 2025;2430.

How to cite this article: Dhoble SS. Understanding AI adoption in business: Benefits, barriers, and future adoption intention: An empirical study of Indian businesses. *International Journal of Agriculture Extension and Social Development*. 2026;9(9):924-932. doi: <https://www.doi.org/10.33545/26180723.2026.v9.i9.1.4297>