“Artificial intelligence in innovation activities: Firm practices and managerial perspectives in Kazakhstan”

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ARTIFICIAL INTELLIGENCE IN INNOVATION ACTIVITIES: FIRM PRACTICES AND MANAGERIAL PERSPECTIVES IN KAZAKHSTAN

Abstract

Artificial intelligence (AI) is increasingly used in innovation activities, yet firm-level evidence on variation across innovation stages and organizational conditions remains limited in emerging economies such as Kazakhstan. This study examines AI use among surveyed firms in Kazakhstan, focusing on stage-specific influence, organizational correlates, barriers, reported effects, and managerial perceptions. A cross-sectional voluntary survey yielded a non-probability sample of 93 firms; data were analyzed using descriptive statistics, reliability analysis, Friedman and Wilcoxon tests, exploratory bivariate analysis, multinomial logistic regression, and descriptive review of open-ended recommendations. In the sample, 39.8% reported no AI use in innovation activities; 23.7% used AI frequently or always. Idea generation was rated higher than idea testing and selection (r = .398), although concordance in stage rankings was weak (Kendall's W = .077). The reported AI-related resource-category count was associated with both occasional (RRR = 6.98) and frequent AI use (RRR = 7.10) relative to no reported AI use in innovation activities. At the same time, firm size and age were not significant. Skills shortages, financial constraints, regulatory uncertainty, and ethical concerns were the leading barriers. Among firms reporting AI use in innovation activities, the most frequently reported effects were greater innovation-process efficiency (46.4%) and improved understanding of industry opportunities and trends (30.4%). The findings provide exploratory firm-level evidence and highlight the relevance of organizational resource support, pilot-based implementation, and human oversight.

Keywords artificial intelligence adoption, innovation management, organizational resources, managerial perceptions, emerging economy, Kazakhstan

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INTRODUCTION

Artificial intelligence (AI) is increasingly integrated into innovation management, influencing how firms generate, evaluate, develop, and commercialize innovations in products, processes, and services. AI can support information processing, experimentation, concept testing, and decision-making across multiple stages of the innovation process and can also alter the division of tasks between managers and AI systems (Cooper, 2024; Gama & Magistretti, 2025; Bessant & Zhidebekkyzy, 2026; Vallé et al., 2026). Data from the Organization for Economic Co-operation and Development (OECD) indicate that the average share of enterprises with 10 or more employees using AI increased from 5.6% in 2020 to 14.0% in 2024; in 2024, AI use reached about 40% among large enterprises compared with 11.9% among small enterprises (OECD, 2025).

At the firm level, AI adoption is constrained by complementary requirements related to data, skills, connectivity, and finance (OECD, 2025; OECD et al., 2025). Kazakhstan provides a relevant setting for examining these issues. The country has adopted the Concept for

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Digital Transformation, Development of the Information and Communication Technologies Sector, and Cybersecurity for 2023–2029 and the Concept for Artificial Intelligence Development for 2024–2029 (Government of the Republic of Kazakhstan, 2023, 2024). Official enterprise statistics nevertheless indicate that organizational AI use remains limited nationally (Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan, 2026).

The scientific problem extends beyond whether firms adopt AI to how its use is distributed across innovation activities and what organizational conditions accompany more intensive use. Recent research maps AI applications across different stages of the innovation process, but direct firm-level comparisons of AI influence across these stages remain limited (Truong & Papagiannidis, 2022; Vallé et al., 2026). In Kazakhstan, existing studies document uneven digital readiness, sectoral differences, and selected applications of AI, but provide limited evidence linking AI-use intensity and organizational resource support with its stage-specific role in innovation (Kurmanov et al., 2022; Golubtsov et al., 2025; Satpayeva et al., 2025). This gap limits understanding of how AI becomes integrated into firm-level innovation processes in an emerging-economy context.

1. LITERATURE REVIEW

Understanding variation in firm-level AI use requires attention to the organizational and contextual conditions surrounding technology adoption. The technology–organization–environment (TOE) framework provides an appropriate organizational-level lens because it distinguishes technological, organizational, and environmental contexts of technology adoption (Tornatzky & Fleischer, 1990). This perspective is more closely aligned with the present firm-level focus than individual-level acceptance models such as TAM and UTAUT, which primarily explain users' perceptions, behavioral intentions, and technology acceptance (Davis, 1989; Davis et al., 1989; Venkatesh et al., 2003). Empirical applications of TOE to AI adoption have identified infrastructure, organizational awareness and readiness, management approaches, competitive conditions, and regulation as relevant factors, although their importance varies across settings and firms (Baabdullah et al., 2021; Yang et al., 2024). In the present study, TOE serves as an interpretive lens and is not operationalized as a three-context explanatory model. The primary analytical emphasis is on the organizational context, particularly firm characteristics and reported AI-related resource support. Technological applications and broader sectoral and institutional conditions provide contextual interpretation. Because TOE-based adoption research provides limited insight into how AI use may differ across specific stages of innovation, this perspective is complemented by a stage-based view of idea generation, idea testing and selection, experimentation and development, and marketing and commercialization.

At the idea-generation stage, AI can expand firms' search space by processing large volumes of information, recombining existing knowledge, and generating alternative concepts rapidly (Cooper, 2024; Kaczorowska-Spychalska et al., 2024; Pescher & Tellis, 2025). Generative AI can match or outperform expert workshops in terms of idea novelty, although the resulting ideas may be less feasible (Eisenreich et al., 2024). It can also support divergent thinking by reducing cognitive fixation (Hou et al., 2025). In parallel, AI-based need-mining approaches can extract customer requirements from unstructured user-generated content, providing additional inputs for product ideation (Ettrich et al., 2024).

At the idea testing and selection stage, AI can reduce information overload and support more systematic evaluation of innovation proposals. Füller et al. (2022) argue that AI-based analysis can enhance idea evaluation by drawing on broader information and helping firms identify promising alternatives. Bell et al. (2024) empirically demonstrate that machine-learning models can pre-sort large idea pools and substantially reduce expert workload while retaining high-potential proposals. However, final selection continues to require managerial judgment to account for context, uncertainty, and strategic fit.

At the experimentation and development stage, AI can accelerate the transformation of concepts into testable solutions. Generative AI enables nontechnical teams to create and refine digital prototypes, reducing iteration cycles and development costs (Bilgram & Laarmann, 2023). AI-enabled digital twins provide virtual representations of products and processes that can support simulation, monitoring, and design improvement before physical development (Fukawa & Rindfleisch, 2023). Interconnected digital twins can further integrate real-time data across actors, enabling continuous testing, prediction, and innovation-oriented decision-making (van Dyck et al., 2023).

At the marketing and commercialization stage, AI can support more targeted, adaptive, and data-driven market launch activities. Generative AI can personalize marketing content, offers, and recommendations at scale, thereby supporting customer engagement and sales lead generation (Kshetri et al., 2024). AI can also enhance product launches through customer segmentation, advertising optimization, and monitoring of competitors' promotional and pricing strategies (Roberts & Candi, 2024). Following launch, conversational AI can process customer requests and analyze interactions, contributing to the identification of opportunities for subsequent product or service improvement (Holmström & Carroll, 2025). However, firms' ability to realize these stage-specific benefits is influenced by the organizational resources and contextual conditions surrounding AI adoption and use.

Empirical TOE research indicates that AI adoption is shaped by both structural firm characteristics and complementary organizational resources and capabilities. Evidence on structural firm characteristics is mixed. Kinkel et al. (2022) found that firm size, digital skills, and R&D intensity were important organizational prerequisites for AI adoption. In contrast, Roberts and Candi (2024) reported no association with firm size but found higher AI use among younger firms, alongside differences across industries. Evidence from emerging economies further emphasizes the importance of organizational capabilities. Among Malaysian SMEs, organizational readiness and top-management commitment were significantly associated with AI adoption, whereas competitive pressure, employee adaptability, and external support were not (Lada et al., 2023). Evidence from Romanian SMEs likewise highlights the importance of leadership and organizational readiness, alongside competitive and customer pressures, and identifies digital-skill deficits as an important barrier (Apostoaie et al., 2025). Taken together, the evidence does not identify structural firm characteristics as consistent correlates of AI adoption across settings and points to the additional relevance of organizational readiness, skills, resources, and managerial support.

AI adoption barriers commonly include shortages of qualified personnel, inadequate or poor-quality data, high implementation costs, difficulties integrating AI into existing processes, regulatory uncertainty, and ethical concerns. Oldemeyer et al. (2025) identify a broad range of implementation challenges, with lack of knowledge, high costs, and inadequate infrastructure among the most frequently reported barriers for SMEs. Zavodna et al. (2024) likewise identify lack of trust, knowledge gaps, infrastructure limitations, and shortages of skilled professionals among SMEs in the Czech Republic and Austria. Evidence from Northern Thailand further points to financial constraints, limited AI skills, and weak data foundations as important adoption challenges (Boonmee et al., 2025). Collectively, these studies indicate that human-capital, financial, data-related, and institutional constraints can be particularly consequential for SMEs and firms operating in less mature digital environments.

Managerial assessments of AI also extend beyond adoption barriers to questions of how AI changes work, decision-making, and human responsibility. The automation–augmentation perspective emphasizes that AI may substitute for some tasks while complementing human judgment in others, creating continuing tensions around the appropriate division of responsibilities between people and intelligent systems (Raisch & Krakowski, 2021). Evidence from AI-intensive settings similarly points to simultaneous opportunities and concerns involving skills, ethical responsibility, authorship, and the preservation of human creativity (Schinello, 2025). These considerations make managerial perceptions relevant to understanding how firms evaluate AI's broader implications alongside its immediate organizational uses.

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Research on Kazakhstan points to heterogeneous patterns of digital and innovation development but provides limited firm-level evidence on AI adoption and use. Satpayeva et al. (2025) identify regional and sectoral disparities in enterprises' digital readiness, including differences in the availability of IT specialists, adoption of advanced technologies, and process automation. Kurmanov et al. (2022) similarly show that organizational digitalization remains uneven and differs across regional and economic contexts. Golubtsov et al. (2025) show that AI remains relatively infrequently used among Kazakhstani logistics firms compared with more established digital technologies. Recent evidence from Kazakhstan's public sector likewise identifies data limitations, skills gaps, infrastructure constraints, and regulatory uncertainty as key barriers to broader AI adoption (Zhidebekkyzy et al., 2026). Yet, this literature provides limited firm-level evidence linking the intensity of AI use and organizational resource support with stage-specific AI applications, adoption barriers, reported outcomes, and managerial assessments of its broader implications.

Overall, the literature shows that AI can support multiple stages of the innovation process, but evidence remains fragmented regarding how its perceived influence differs across stages within firms. Findings on firm characteristics are also inconsistent across settings; organizational readiness, skills, infrastructure, and complementary resources repeatedly emerge as relevant correlates of AI adoption and use. In Kazakhstan, existing research documents uneven digital readiness and selected sectoral applications of AI but provides limited firm-level evidence integrating stage-specific AI use with organizational resource support, implementation barriers, reported outcomes, and managerial assessments.

Accordingly, the aim of this study is to examine how AI is used in firms' innovation activities in Kazakhstan by assessing its perceived influence across innovation stages, its associations with firm characteristics and organizational resource support, and managers' assessments of implementation barriers, outcomes, plans, and broader industry implications.

The study addresses the following research questions:

RQ1. At which stages of the innovation process is AI perceived to exert the greatest and least influence, and do these assessments differ significantly across stages within firms?

RQ2. How are firm characteristics and reported AI-related resource support associated with the intensity of AI use in innovation activities?

RQ3. What barriers, reported effects, and plans characterize firms' use of AI in innovation activities?

RQ4. How do managers perceive the broader implications of AI for innovation within their industries, and what recommendations do they offer for its effective application?

2. METHOD

This study used a cross-sectional, firm-level survey design to examine the use of artificial intelligence (AI) in the innovation activities of companies operating in Kazakhstan. The firm was the unit of analysis, and top- and middle-level managers served as organizational informants. A non-probability, voluntary-response approach was used. Data were collected from October 2025 to March 2026 through an online questionnaire disseminated with the support of business associations and public agencies responsible for industry and enterprise development, as well as through professional networks and social media. Respondents were informed about the study purpose and confidentiality arrangements. The study protocol was approved by the local ethics committee (approval no. IRB-A1717, September 18, 2025).

The questionnaire was developed from the conceptual dimensions identified in the literature review and comprised 16 questions using single-response, multiple-response, scale-based, and open-ended formats (Füller et al., 2022; Roberts & Candi, 2024). Questions on barriers, reported effects, and plans were administered to all respondents irrespective of their reported AI-use frequency. Barriers were analyzed as perceived obstacles to AI adoption or use, while plans represented stated intentions. Because the multiple-

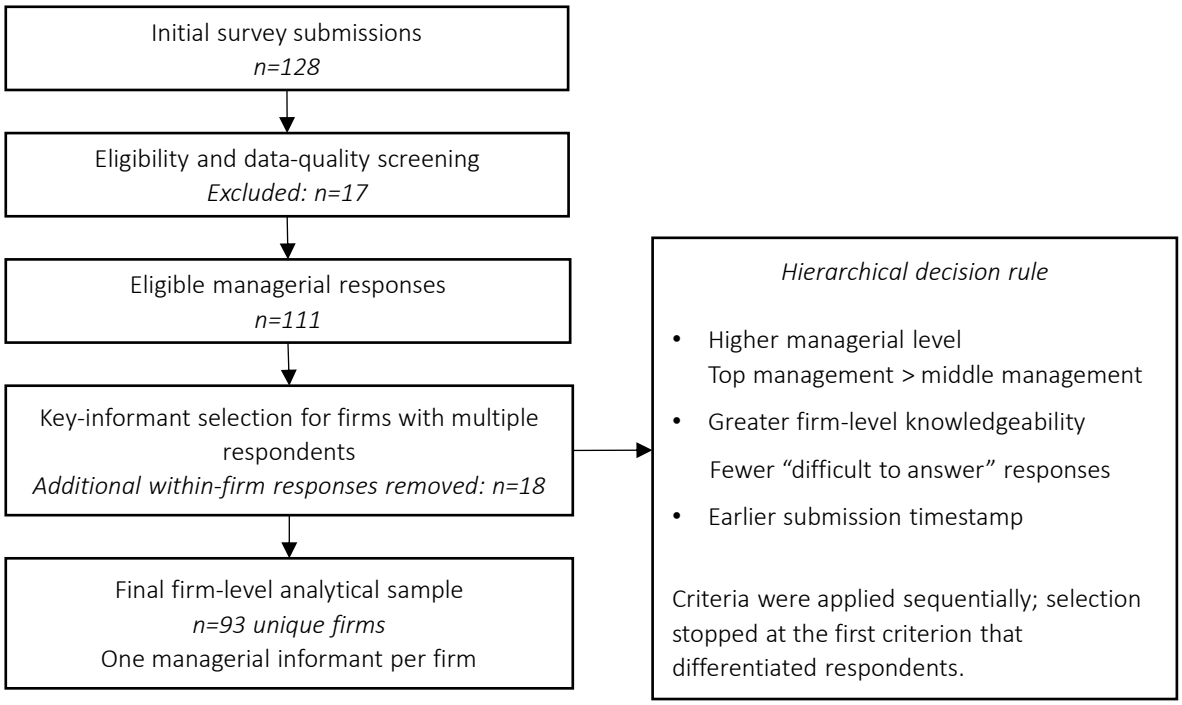

Figure 1. Sample screening and key-informant selection process

response reported-effects block concerned outcomes of AI use in innovation activities, frequencies for this block were summarized for firms reporting AI use in innovation activities (n = 56). The separate item assessing the perceived influence of AI on firm profitability was analyzed for the full sample (n = 93).

Of 128 submitted questionnaires, 17 were excluded because the respondent did not represent an eligible firm, the questionnaire was substantially incomplete, or the company could not be identified reliably. This yielded 111 eligible managerial responses. Where a firm was represented by more than one respondent, one key informant was retained using a pre-specified, hierarchical and non-compensatory rule informed by key-informant research (Kumar et al., 1993; Homburg et al., 2012). Criteria were applied sequentially: higher managerial level (top over middle), fewer "difficult to answer" responses in the firm-level knowledge blocks, and earlier submission time. The rule was applied before multiple-response variables were prepared or open-ended responses were reviewed. Removing 18 duplicate within-firm responses produced a final sample of 93 firms, each represented by one managerial informant (Figure 1).

The final analytical sample covered firms of different sizes, ages, sectors, and geographic macroregions of Kazakhstan. Top managers represented 45.2% of the managerial informants and middle managers constituted 54.8%. Firm and informant characteristics are summarized in Table 1.

For the innovation-stage analysis, responses coded as 0 ("difficult to answer") were treated as missing. Four composite scores were calculated as the arithmetic means of their corresponding items: idea generation, idea testing and selection, experimentation and development, and marketing and commercialization. Scores were computed when at least three of four items were valid for idea generation, at least five of six for idea testing and selection, and at least four of five for each remaining stage. Internal consistency was assessed separately using Cronbach's alpha, corrected item-total correlations, inter-item correlations, and alpha coefficients after item deletion (Cortina, 1993). The four-stage scores were not combined because the analysis compared perceived AI influence across stages. The Friedman analysis included firms with valid scores for all four stages (n = 46).

The original five-category AI-use-frequency measure was retained for descriptive analysis and re-

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Table 1. Characteristics of the surveyed firms and managerial informants

Characteristic	Category	n	%
Managerial position of informant	Top management	42	45.2
	Middle management	51	54.8
Geographic macroregion	Western Kazakhstan	18	19.4
	Northern Kazakhstan	19	20.4
	Eastern Kazakhstan	4	4.3
	Central Kazakhstan	3	3.2
	Southern Kazakhstan	49	52.7
Firm size	Small	38	40.9
	Medium-sized	13	14.0
	Large	42	45.2
Firm age	Less than 5 years	20	21.5
	5–10 years	18	19.4
	More than 10 years	55	59.1
Sector group	Production and infrastructure	28	30.1
	Trade, transport and hospitality	16	17.2
	Knowledge-intensive and business services	12	12.9
	Social and cultural services	11	11.8
	Other sectors	26	28.0

Note: Percentages are based on the full analytical sample (n = 93) and may not sum to 100% due to rounding.

coded for multivariable modeling into non-use, occasional use ("rarely" or "sometimes"), and frequent use ("frequently" or "always"). The AI-use-frequency measure referred specifically to AI use in innovation activities. Accordingly, the non-use category denotes no reported AI use in innovation activities and does not imply the absence of AI use for other organizational purposes. The organizational resource measure was operationalized as the number of predefined AI-related resource categories reported for each firm: dedicated AI or machine-learning budgets, cloud or data resources, employee training, external consulting, and AI-related R&D. Because respondents could select no more than three options, the resulting resource-category count ranged from 0 to 3 and should not be interpreted as a comprehensive measure of organizational resource breadth. "Other" was excluded because it did not represent a uniform resource category. Multiple-response results were calculated as percentages of firms, not percentages of selections; therefore, percentages did not sum to 100%. A separate multiple-response item asked about the purposes for which firms used AI technologies more broadly and was analyzed independently of the innovation-specific AI-use-frequency measure. Q15 statements were analyzed separately and were not combined into a scale. "Difficult to answer" responses were reported separately and excluded from the calculation of means, standard deviations, and medians. No statistical imputation was performed.

Statistical analyses were conducted in IBM SPSS Statistics 25. Descriptive statistics included frequencies, percentages, means, standard deviations, medians, and interquartile ranges where appropriate. Differences across the four innovation stages were tested using the Friedman test. Kendall's W was reported as the coefficient of concordance, indicating agreement among firms in their ranking of the stages (Kendall & Babington Smith, 1939). A significant omnibus result was followed by six two-sided Wilcoxon signed-rank tests with Holm adjustment (Holm, 1979). Pairwise effect sizes were calculated as $r = |Z|/\sqrt{N}$, where N was the number of paired observations ($N = 46$); values near .10, .30, and .50 were interpreted as small, medium, and large (Fritz et al., 2012). Firms included in the complete-stage analysis were compared with the remaining firms using Mann-Whitney U tests for size, age, and AI-use intensity and chi-square tests for sector composition, managerial position, and availability of AI-budget information.

Exploratory bivariate associations were examined using Spearman's rank correlation, Mann-Whitney U tests for binary resource indicators and

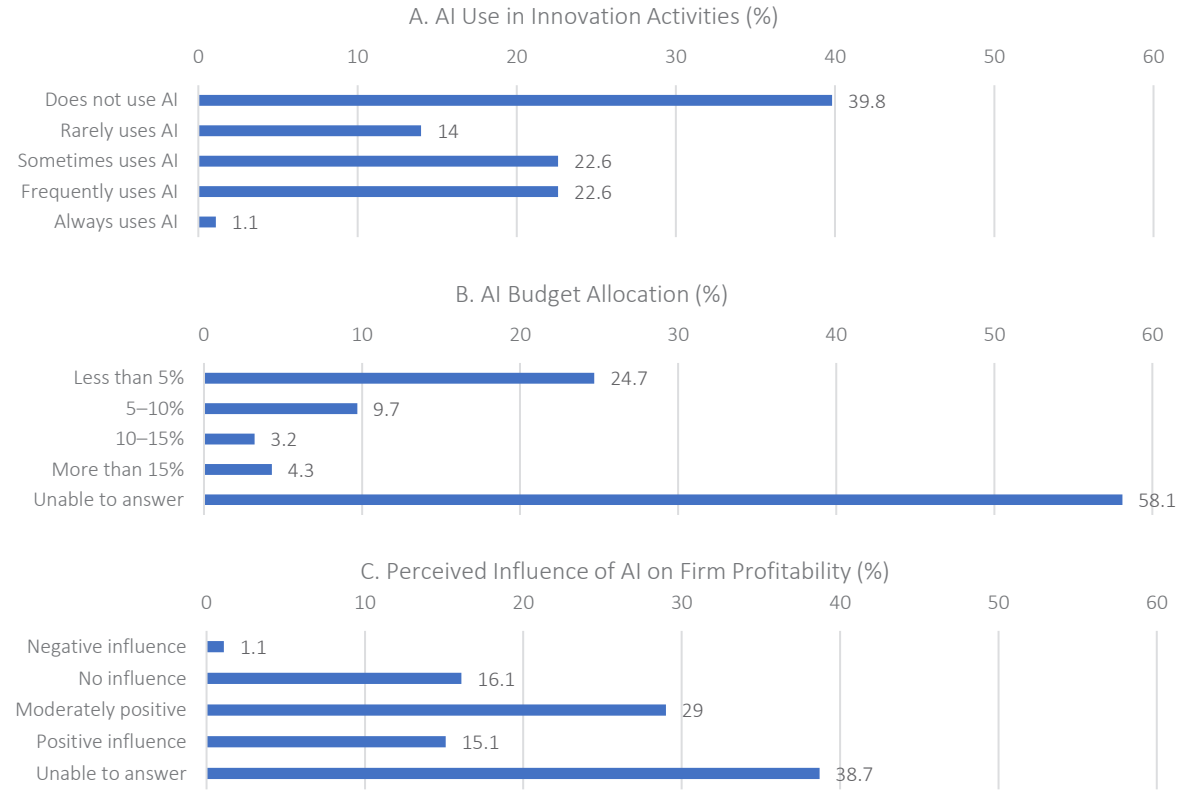
budget-information availability, and the Kruskal-Wallis test for sector differences. Except for the six resource-category comparisons, for which Holm adjustment was applied, nominal p-values were interpreted descriptively. The three-category outcome comprised non-use (n = 37), occasional use (n = 34), and frequent use (n = 22). An initial ordinal logistic model including firm size, firm age, and reported resource-category count failed the proportional-odds assumption (test of parallel lines: $\chi^2(5) = 12.348$, $p = .030$). Multinomial logistic regression was therefore used, with non-use as the reference outcome and the same three predictors (Agresti, 2013). Firm size and age were categorical, while reported resource-category count was continuous. Across two logits, the model estimated 10 predictor coefficients plus two intercepts. Given the small frequent-use group and sparse predictor-response combinations, estimates were interpreted as explanatory, not predictive. Accordingly, emphasis was placed on the direction and uncertainty of the associations, with less emphasis on the magnitude of individual RRR estimates. Relative risk ratios and 95% confidence intervals were reported. A binary logistic model contrasting any reported AI use in innovation activities with no reported use in innovation activities and using the same predictors served as a robustness check. All tests were two-sided; $p < .05$ was used for the primary inferential analyses.

Open-ended recommendations were reviewed descriptively and synthesized to complement the quantitative findings and provide additional context for the discussion.

3. RESULTS

3.1. AI adoption profile

Within the surveyed sample, AI use in innovation activities varied considerably. Overall, 39.8% of firms reported no AI use in innovation activities, 14.0% used AI rarely, 22.6% sometimes, 22.6% frequently, and 1.1% always. The three-category outcome used in the multivariable analysis therefore comprised 37 firms reporting no AI use in innova-



Note: Values represent percentages of the full analytical sample (n = 93). Percentages may not sum to 100 because of rounding.

Figure 2. Corporate AI adoption profile: Use intensity, budget allocation, and perceived influence of AI on firm profitability

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tion activities, 34 occasional users, and 22 frequent users. More than half of the informants (58.1%) were unable to specify the share of the firm's budget allocated to AI. Among the full sample, 24.7% reported an allocation below 5%, 9.7% between 5% and 10%, 3.2% between 10% and 15%, and 4.3% above 15%. Regarding the perceived influence of AI on firm profitability, 1.1% reported a negative influence, no respondent reported a moderately negative influence, 16.1% reported no influence, 29.0% reported a moderately positive influence, 15.1% reported a positive influence, and 38.7% were unable to provide an assessment (Figure 2).

Across the broader organizational-use item, the most frequently reported purpose of AI use was the automation of routine processes (50.5%), followed by big-data analysis (33.3%), improved customer service (20.4%), and human-resource management optimization (17.2%) (Figure 3).

In terms of organizational support, employee AI training was selected by 34.4% of firms, dedicated budgets for AI or machine-learning projects by 32.3%, and cloud or data resources by 20.4%. External consultancy partnerships and AI-related R&D investment were selected by 10.8% and 7.5%, respectively (Table 2).

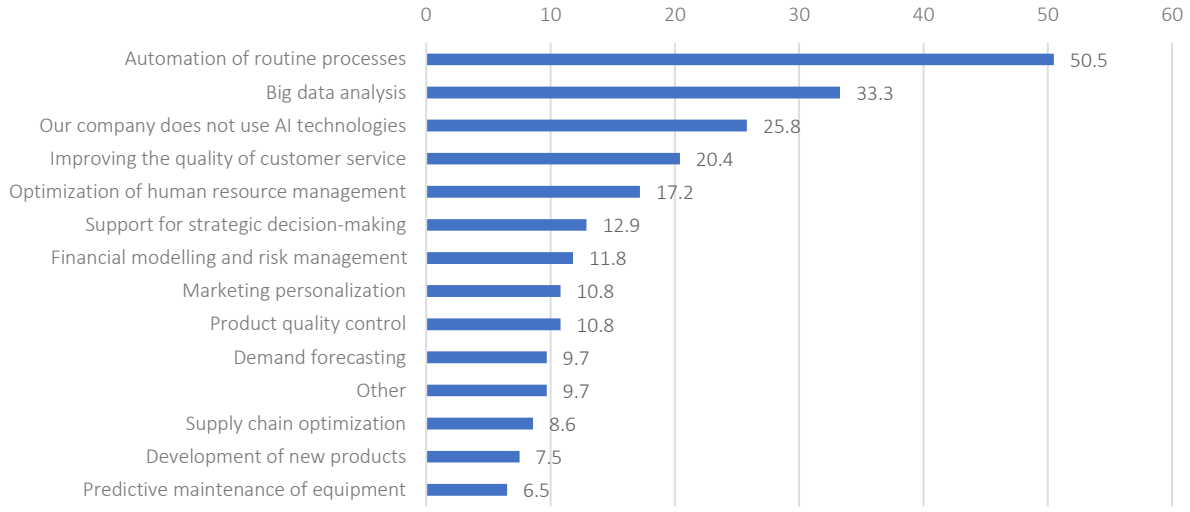
3.2. Perceived AI influence across innovation stages

The four stage-specific measures showed high internal consistency. Cronbach's alpha was .909 for idea generation (n = 52), .960 for idea testing and selection (n = 49), .963 for experimentation and development (n = 55), and .974 for marketing and commercialization (n = 55). Corrected item-total correlations ranged from .713 to .944 across the four measures, and deletion of individual items did not materially increase the alpha coefficients.

Table 2. AI-related organizational resources reported by surveyed firms

Resource category	n	Firms (%)
AI training programs for employees	32	34.4
Budgets allocated to AI and machine-learning projects	30	32.3
Other	21	22.6
Cloud and data resources, such as AWS and Google Cloud	19	20.4
Partnerships with external AI consultants	10	10.8
R&D investment in AI	7	7.5

Note: Respondents could select up to three options. Percentages represent the proportion of firms selecting each resource category (n = 93) and therefore do not sum to 100%.



Note: Multiple responses were permitted. Percentages represent the proportion of firms selecting each option (n = 93) and therefore do not sum to 100%. This item concerned organizational uses of AI broadly and was analyzed separately from the innovation-specific AI-use-frequency measure.

Figure 3. Reported organizational purposes of AI use among surveyed firms (%)

Table 3. Perceived AI influence across innovation stages: Descriptive statistics and Friedman test results

Innovation stage	M	SD	Median	Q1–Q3	Mean rank
Idea generation	2.93	1.38	2.88	1.50–4.25	2.89
Idea testing and selection	2.75	1.38	2.67	1.33–3.83	2.17
Experimentation and development	2.76	1.42	2.43	1.55–4.20	2.38
Marketing and commercialization	2.99	1.52	3.00	1.40–4.60	2.55

Note: Results are based on firms with valid composite scores for all four innovation stages (n = 46). Higher values indicate stronger perceived AI influence. Overall comparison: Friedman $\chi^2(3) = 10.645$, p = .014; Kendall's W = .077, indicating weak concordance among firms in their ranking of the stages. Full pairwise comparisons, including effect sizes, are reported in Appendix A, Table A1.

Mean inter-item correlations were .715, .800, .840, and .882, respectively, indicating particularly strong item homogeneity in the later-stage measures.

The within-firm comparison was based on 46 firms with valid composite scores for all four stages. Arithmetic mean scores were relatively close: marketing and commercialization had the highest mean (M = 2.99, SD = 1.52), followed by idea generation (M = 2.93, SD = 1.38), experimentation and development (M = 2.76, SD = 1.42), and idea testing and selection (M = 2.75, SD = 1.38). Friedman mean ranks were highest for idea generation (2.89) and lowest for idea testing and selection (2.17), as shown in Table 3.

The Friedman test indicated a statistically significant overall difference across the four stages, $\chi^2(3) = 10.645$, $p = .014$. Kendall's W = .077 indicated weak concordance among firms in their ranking of the stages; thus, the significant omnibus result did not reflect a strongly shared stage hierarchy across the sample. Pairwise Wilcoxon signed-rank tests with Holm adjustment showed that only the difference between idea generation and idea testing and selection remained statistically significant ($Z = –2.702$, Holm-adjusted $p = .042$, $r = .398$). Idea generation was rated higher in 24 firms, idea testing and selection was rated higher in nine firms, and 13 firms reported equal scores. The comparison between idea generation and experimentation and development also produced a medium effect ($Z = –2.451$, $r = .361$), but it did not remain statistically significant after adjustment (Holm-adjusted $p = .070$). The remaining comparisons had negligible or small effects ($r = .036–.239$) and were not statistically significant after adjustment. Full pairwise results are reported in Appendix A, Table A1.

No statistically significant differences were detected between the 46 firms included in the complete-stage analysis and the remaining firms in size (U = 1080, $p = .993$), age (U = 1035, $p = .688$), industry composition ($\chi^2(4) = 3.746$, $p = .442$), or managerial position ($\chi^2(1) = 0.009$, $p = .925$). AI-use intensity was somewhat higher among complete-stage firms, although the difference did not reach statistical significance (U = 868, $p = .086$). Informants in the complete-stage subsample were more likely to provide information on their firm's AI budget allocation than those in the remaining sample (52.2% vs. 31.9%; $\chi^2(1) = 3.918$, $p = .048$).

3.3. Firm resources and the intensity of AI use

Exploratory bivariate analyses showed a weak positive association between AI-use intensity and firm size ($\rho = .220$, $p = .034$), but no association with firm age ($\rho = .049$, $p = .641$). A positive association was observed for the reported AI-related resource-category count ($\rho = .385$, $p < .001$). Among the 39 firms for which budget information was available, the reported AI budget share was positively associated with use intensity ($\rho = .365$, $p = .022$). Firms whose informants could specify the AI budget share also showed higher use intensity than firms whose informants were unable to provide this information (U = 750.5, $p = .014$). Except for the resource-category comparisons subjected to Holm adjustment, these nominal p-values are reported descriptively and should not be interpreted as confirmatory evidence.

Across the six resource-category comparisons, Holm adjustment was applied to control for multiplicity. Firms reporting dedicated AI or machine-learning project budgets showed higher AI-use in-

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Table 4. Multinomial logistic regression of AI-use intensity

Predictor	Occasional use vs. non-use RRR (95% CI)	P	Frequent use vs. non-use RRR (95% CI)	p	Overall LR p
Reported AI-related resource-category count (0–3)	6.98 (2.48–19.67)	<.001	7.10 (2.38–21.15)	<.001	<.001
Small firm vs. large firm	0.66 (0.15–2.84)	.579	0.25 (0.05–1.29)	.098	.116
Medium-sized firm vs. large firm	1.10 (0.21–5.88)	.912	0.11 (0.01–1.40)	.090	.116
Firm age ≤5 years vs. >10 years	1.28 (0.26–6.27)	.762	1.65 (0.25–10.78)	.604	.691
Firm age 5–10 years vs. >10 years	0.58 (0.11–3.04)	.518	1.83 (0.31–10.74)	.503	.691

Note: n = 93. The reference outcome was no reported AI use in innovation activities. RRR = relative risk ratio; CI = confidence interval; LR = likelihood-ratio test. Reference categories were large firms and firms operating for more than ten years. "Other" was excluded from the resource-category count. Overall model: $\chi^2(10) = 37.952$, $p < .001$, Nagelkerke $R^2 = .379$.

tensity (U = 626.5, unadjusted $p = .006$), and this difference remained statistically significant after adjustment. Employee AI training alone was not associated with use intensity (U = 953.0, $p = .845$). The heterogeneous 'Other' category also remained significant after adjustment but was associated with lower AI-use intensity; because it combined substantively different responses, it was not interpreted and was excluded from the reported resource-category count. No statistically significant sector differences were detected, Kruskal–Wallis $H(4) = 9.163$, $p = .057$.

A multinomial logistic regression was estimated using all 93 firms, with no reported AI use in innovation activities as the reference outcome. The model significantly improved upon the intercept-only specification, $\chi^2(10) = 37.952$, $p < .001$, and produced a Nagelkerke pseudo-R^2 of .379. The reported resource-category count was the only statistically significant overall predictor, likelihood-ratio $\chi^2(2) = 25.570$, $p < .001$. Each additional reported resource category was associated with a higher relative likelihood of occasional AI use relative to non-use (RRR = 6.98, 95% CI [2.48, 19.67], $p < .001$) and frequent use relative to non-use (RRR = 7.10, 95% CI [2.38, 21.15], $p < .001$). The wide confidence intervals indicate substantial uncertainty in the magnitude of these associations. Moreover, the similar RRR estimates for occasional and frequent use suggest that the resource-category count primarily differentiated firms reporting AI use in innovation activities from those reporting no such use, while distinguishing less clearly between occasional and frequent use. Firm size was not statistically significant as an overall effect, $\chi^2(4) = 7.413$, $p = .116$, and firm age was unrelated to AI-use intensity, $\chi^2(4) = 2.245$, $p = .691$. Given the relatively small frequent-user group ($n = 22$) and sparse response-by-predictor combinations, the coefficient estimates, particularly those for firm size and age, should be interpreted cautiously (Table 4).

The model correctly classified 53.8% of cases and showed lower classification accuracy for frequent users than for occasional users, reinforcing its interpretation as an explanatory rather than predictive model. A binary logistic regression using the same predictors and contrasting any reported AI use in innovation activities with non-use in innovation activities confirmed the association with the reported AI-related resource-category count (OR = 7.22, 95% CI [2.68, 19.43], $p < .001$). The binary model showed acceptable fit (Hosmer–Lemeshow $\chi^2(7) = 4.384$, $p = .735$); firm size and age remained non-significant.

3.4. Reported barriers, effects, and plans

Across the full sample, 89.2% of managerial informants selected at least one barrier related to AI adoption or use in innovation activities, and 10.8% selected "No difficulties." The most prevalent barriers were a shortage of qualified personnel for developing and using AI solutions (36.6%), insufficient financial resources (29.0%), deficiencies in the AI-related regulatory framework (25.8%), and ethical concerns (24.7%). Operational and technological constraints, including data-infrastructure maturity, integration difficulties, privacy, data quality, and computing capacity, were selected less frequently.

Among the 56 firms reporting AI use in innovation activities, 91.1% reported at least one specific effect, while 8.9% selected "No effects obtained." The most frequently reported effect was the accel-

eration of innovation processes and improvement in their efficiency (46.4%), followed by a more accurate understanding of industry opportunities and trends (30.4%). Faster and more efficient introduction of products or services to the market was reported by 17.9% of these firms, while the development of higher-quality products or services and increased employee job satisfaction were each reported by 14.3%. The remaining specific effects were reported by 10.7% or fewer of these firms.

Across the full sample, plans were predominantly expansion-oriented. The most prevalent intention was to expand AI use across core and supporting business processes (40.9%), followed by integrating AI into corporate strategy (35.5%) and continuing or initiating the development of innovative products or services using AI (24.7%). Increasing AI investment and collaborating with universities, start-ups, or IT companies were each selected by 14.0% of firms, while 9.7% planned to develop AI solutions in-house. Plans to reduce or completely discontinue AI use were rare. These results represent stated managerial intentions rather than completed actions. Full distributions of barriers, effects, and plans are reported in Appendix A, Table A2.

3.5. Industry-level perceptions, implications, and managerial recommendations

Managers expressed a predominantly positive view of AI within their industries. Overall, 75.3% perceived AI as an opportunity, including 55.9% who viewed it more as an opportunity and 19.4% who viewed it definitely as an opportunity. A further 22.6% reported a neutral position, while only 2.2% perceived AI more as a threat. No respondent selected the "definitely a threat" category. Both the median and modal response corresponded to "more of an opportunity."

Positive overall perceptions did not imply an absence of concern. Although 17.2% of managerial informants selected 'No threats,' 82.8% selected at least one specific industry-level risk. The most frequently selected threats were deterioration of analytical-thinking skills (31.2%), diffusion of responsibility for the negative consequences of AI-supported decisions (25.8%), job losses (22.6%), cybersecurity threats and vulnerabilities (21.5%), displacement of human creativity (20.4%), and technological dependence and loss of research competencies (19.4%).

At the same time, 94.6% of managerial informants selected at least one concrete industry-level opportunity associated with AI. The most frequently selected opportunities were improved efficiency of teams and business models (41.9%), redistribution of routine tasks to AI (32.3%), generation of new ideas and unconventional solutions (31.2%), advanced analysis of large datasets and trend forecasting (30.1%), and faster introduction of products and services to the market (25.8%).

Among the five managerial assessment statements, respondents expressed the strongest agreement that AI reduces the time required to develop new products, services, or processes ($M = 3.35$, $SD = 1.31$, median = 4); 51.2% of respondents provided a substantive rating of agreement or strong agreement. Mean assessments of the novelty and value of AI-generated ideas ($M = 2.95$), improved understanding of customer needs and market trends ($M = 2.83$), reduction of innovation risks ($M = 3.00$), and the ethical acceptability of AI use in innovation ($M = 2.95$) were close to the neutral midpoint. Uncertainty was highest for AI's ability to reduce innovation risks, for which 18.3% of respondents were unable to provide an assessment. Full distributions are presented in Appendix A, Table A3.

The open-ended recommendations further contextualized the industry-level findings. Managers' comments addressed several practical aspects of AI implementation, including AI literacy and role-specific competencies, clearly defined business or innovation use cases, pilot-based implementation and subsequent scaling, data quality and digital infrastructure, and human oversight. Respondents referred to the need to formulate appropriate tasks, interpret AI outputs, recognize ethical and security risks, define measurable objectives, and ensure adequate data and process readiness. The comments also identified fragmented data, weak connectivity, and poorly organized processes as implementation constraints and emphasized data protection, model auditing, and clear responsibility for consequential decisions. AI was described as an analytical or generative assistant whose out-

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puts require human evaluation and accountability. The comments also included examples related to automation, cost reduction, forecasting, data processing, equipment diagnostics, idea development, experimentation, product development, and commercialization.

4. DISCUSSION

The findings provide a differentiated answer to the four research questions. The stage-level analysis showed statistically significant variation in perceived AI influence, but the weak Kendall's W indicates that firms did not share a strong common hierarchy across innovation stages. Idea testing and selection had the lowest arithmetic mean and Friedman mean rank, whereas the stage with the highest perceived influence depended on the summary metric: marketing and commercialization had the highest arithmetic mean; idea generation had the highest mean rank. After adjustment for multiple comparisons, only idea generation was rated significantly higher than idea testing and selection. This pattern is consistent with research showing that AI is particularly suited to information-intensive search, ideation, and generation of alternatives, while evaluation and selection continue to require contextual judgment and human accountability (Haefner et al., 2021; Roberts & Candi, 2024).

The reported AI-related resource-category count showed the clearest association with AI-use category, whereas firm size and age were not statistically significant in the multivariable analysis. The similar RRR estimates for occasional and frequent use indicate that the measure differentiated firms reporting AI use in innovation activities from those reporting no such use more clearly than it differentiated occasional from frequent use. This finding is consistent with conceptualizations of AI capability as a configuration of complementary technological, human, and organizational resources (Mikalef & Gupta, 2021) and with evidence linking organizational readiness and managerial support to AI adoption (Lada et al., 2023; Apostoaie et al., 2025). The high proportion of informants unable to specify AI-budget shares may additionally indicate limited formalization or managerial visibility of AI-related spending. Within the TOE perspective, these findings relate most directly to the organizational context; technological and environmental conditions were not operationalized as parallel predictors, and their relative explanatory importance therefore cannot be assessed.

The main reported barriers concerned skills, finance, regulation, and ethics, broadly consistent with evidence identifying knowledge gaps, implementation constraints, data issues, trust, and social concerns as recurring obstacles to AI adoption (Cubric, 2020; Hangl et al., 2023). Among firms reporting AI use in innovation activities, reported effects were concentrated in improved efficiency and understanding of industry opportunities and trends, with product-development, commercialization, and innovation-risk effects reported less frequently. This pattern parallels cross-country evidence that AI-related activity does not automatically translate into innovation outcomes (Temerbulatova et al., 2025). At the same time, plans across the full sample were predominantly expansion-oriented. These findings indicate uneven development of AI use, with currently reported benefits concentrated in operational and analytical areas, and broader organizational integration remains incomplete.

Managers generally viewed AI as an industry opportunity while simultaneously identifying risks related to analytical skills, accountability, employment, cybersecurity, human creativity, and technological dependence. Cognitive and organizational concerns, including deterioration of analytical thinking and diffusion of responsibility, were among the most frequently reported risks, alongside employment displacement. This pattern is compatible with recent cross-country evidence showing no measurable short-run relationship between national AI vibrancy and employment structures or unemployment, while longer-term effects remain uncertain (Kuzior et al., 2025a, 2025b). The quantitative findings also show a strong operational emphasis: automation of routine processes was the most frequently reported purpose of AI use, and innovation-process efficiency was the most frequently reported effect among firms reporting AI use in innovation activities. The open-ended comments complement this pattern by addressing capability development,

data and process readiness, clearly defined use cases, staged experimentation, governance, and human oversight. Taken together, these observations suggest that effective AI implementation extends beyond technology acquisition and involves organizational capabilities and arrangements that support its responsible integration into innovation activities. The comments concerning continued human responsibility are consistent with the automation–augmentation perspective and evidence that AI-supported work requires human guidance, user competence, and critical evaluation of system outputs (Raisch & Krakowski, 2021; Kurki et al., 2024).

For firms facing similar implementation conditions, the findings point to several practical priorities. AI initiatives should be linked to clearly defined innovation problems and measurable objectives, supported by appropriate skills, data, infrastructure, and governance, and tested through limited pilots before wider scaling. Training needs are likely to differ across organizational roles, from basic AI literacy to task formulation, output verification, project evaluation, integration, security, and ethics. Clear responsibility should also be retained for data protection, output validation, and consequential decisions. Beyond individual firms, industry-specific training, shared experimentation environments, advisory support, and digital infrastructure can help address constraints related to skills, connectivity, and access to applicable AI solutions.

The study has several limitations. Because the sample was voluntary and non-probability, the findings should not be generalized to firms in Kazakhstan as a whole or used to estimate the national prevalence of AI use. The cross-sectional design does not establish the direction of the association between reported resource support and AI use, as resource commitments may precede AI use or expand as firms gain experience with AI. Reliance on a single managerial informant and self-reported measures represents an additional limitation. In addition, the resource-category count was capped at three selections and should not be interpreted as a comprehensive measure of organizational resource breadth. The multinomial estimates remain imprecise because of the small frequent-user group and wide confidence intervals. The stage-level analysis was restricted to firms with valid assessments across all four stages, and the included subsample was more likely to provide AI-budget information, suggesting some selection toward better-informed respondents. The very high inter-item correlations of the later-stage measures may also partly reflect overlap among closely related AI applications within the same innovation stage.

CONCLUSION

This study aimed to examine how firms in Kazakhstan use AI in innovation activities by comparing its perceived influence across innovation stages, assessing associations with firm characteristics and organizational resource support, and examining barriers, reported effects, plans, and managerial perceptions.

The findings showed no strong common hierarchy of AI influence across innovation stages, although idea generation was rated significantly higher than idea testing and selection. The reported AI-related resource-category count was associated with both occasional and frequent AI use in innovation activities relative to no reported use, whereas firm size and age were not statistically significant in the multivariable analysis; the similar RRR estimates indicate that the count mainly distinguished firms using AI in innovation activities from those not using it. Skills shortages, financial constraints, regulatory uncertainty, and ethical concerns were the most frequently reported barriers; firms using AI in innovation activities most often cited faster, more efficient innovation processes and a more accurate understanding of industry opportunities and trends, and future plans across the full sample were predominantly expansion-oriented.

Overall, the results indicate that AI use in innovation activities is associated with reported AI-related resource support and that its perceived influence differs across innovation stages without a common hierarchy among firms. Taken together, the quantitative findings and managers' recommendations

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point to the practical relevance of employee competencies, data and infrastructure readiness, clearly defined use cases, pilot-based implementation, governance, and human oversight when expanding AI-supported innovation activities. Within the TOE perspective, the findings relate most directly to the organizational context and do not establish the relative explanatory importance of technological and environmental conditions.

These conclusions are based on exploratory evidence from a voluntary, non-probability sample of 93 firms and should be interpreted within that scope. Future research should examine these patterns using larger and more representative samples, longitudinal designs, multiple organizational informants, objective indicators of innovation performance, and broader measures of technological and environmental conditions.

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APPENDIX A. Supplementary results

Table A1. Pairwise comparisons of perceived AI influence across innovation stages

Pairwise comparison	Higher-rated stage	Z	Effect size r	Unadjusted p	Holm-adjusted p	Result
Idea generation vs. idea testing and selection	Idea generation	−2.702	.398	.007	.042	Significant; medium effect
Idea generation vs. experimentation and development	Idea generation	−2.451	.361	.014	.070	Not significant after adjustment; medium effect
Idea generation vs. marketing and commercialization	–	−0.241	.036	.809	.972	Not significant; negligible effect
Idea testing and selection vs. experimentation and development	Experimentation and development	−0.697	.103	.486	.972	Not significant; small effect
Idea testing and selection vs. marketing and commercialization	Marketing and commercialization	−1.618	.239	.106	.424	Not significant; small effect
Experimentation and development vs. marketing and commercialization	Marketing and commercialization	−1.565	.231	.118	.424	Not significant; small effect

Note: Pairwise differences were examined using two-sided Wilcoxon signed-rank tests among firms with valid scores for all four stages (N = 46). Effect sizes were calculated as $r=|Z|/\sqrt{N}$, where N denotes the number of paired firm observations. Approximate benchmarks of .10, .30, and .50 indicate small, medium, and large effects, respectively. Holm-adjusted p-values account for six pairwise comparisons.

Table A2. Firm-level barriers, reported effects, and future plans for AI use in innovation activities

Panel A. Reported barriers

Reported barrier	n	% of firms
Shortage of qualified personnel for developing and using AI solutions	34	36.6
Insufficient financial resources for AI development and application	27	29.0
Inadequate AI-related regulatory framework	24	25.8
Ethical concerns, including transparency, explainability, accountability, misinformation, and deepfakes	23	24.7
Insufficient business-process automation and data-infrastructure maturity	13	14.0
Difficulties integrating AI into existing business processes	12	12.9
Difficulties protecting the personal data of customers and employees	10	10.8
Other	10	10.8
No difficulties	10	10.8
High energy intensity of AI technologies	9	9.7
Limited availability and poor quality of data for training AI models	7	7.5
Shortage of computing resources and equipment capacity	6	6.5
Need to reconfigure the operating model and corporate culture	5	5.4
Job losses	3	3.2

Panel B. Reported effects among firms reporting AI use in innovation activities (n = 56)

Reported effect	n	% of AI-using firms (n=56)
Acceleration of innovation processes and improvement in their efficiency	26	46.4
More accurate understanding of opportunities and trends in the industry	17	30.4
Faster and more efficient introduction of products or services to the market	10	17.9
Development of higher-quality products or services	8	14.3
Increased employee job satisfaction	8	14.3
Enhanced company reputation as a technological leader	6	10.7
Reduction of innovation-related risks	6	10.7
Deeper understanding of competitors' activities	5	8.9
Deeper understanding of current and latent consumer needs	4	7.1
Other	3	5.4
No effects obtained	5	8.9

Table A2 (cont.). Firm-level barriers, reported effects, and future plans for AI Use in innovation activities

Panel C. Reported plans		
Reported future plan	**n**	**% of firms**
Expand AI use across core and supporting business processes	38	40.9
Integrate AI into corporate strategy	33	35.5
Continue or initiate the development of innovative products or services using AI	23	24.7
Other	16	17.2
Increase investment in AI technologies for innovation activities	13	14.0
Collaborate with universities, start-ups, or IT companies in implementing AI-based innovation projects	13	14.0
Develop AI solutions in-house	9	9.7
Completely discontinue AI use	3	3.2
Reduce AI use	1	1.1

Note: Panels A and C are based on the full analytical sample (n = 93). Panel B reports effects among firms reporting AI use in innovation activities (n = 56). Respondents could select up to three options in each panel; therefore, percentages within panels do not sum to 100%.

Table A3. Managers' industry-level perceptions and assessments of AI

Panel A. Overall perceptions of AI *n* = 93. Median = 4; mode = 4		
Perception of AI	**n**	**% of firms**
Definitely a threat	0	0.0
More of a threat	2	2.2
Neutral	21	22.6
More of an opportunity	52	55.9
Definitely an opportunity	18	19.4

Panel B. Reported industry-level threats *n* = 93. Respondents could select up to three options; therefore, percentages do not sum to 100%		
Reported threat	**n**	**% of firms**
Deterioration of analytical-thinking skills	29	31.2
Diffusion of responsibility for the negative consequences of AI-supported decisions	24	25.8
Job losses	21	22.6
Cybersecurity threats and vulnerabilities, including hacking and unauthorized access	20	21.5
Displacement of human creativity	19	20.4
Technological dependence and loss of research competencies	18	19.4
No threats	16	17.2
Misinformation and the spread of deepfakes	13	14.0
Loss of control over decision-making due to algorithmic opacity	12	12.9
Unfair decisions affecting customers, employees, or partners	2	2.2
Other	2	2.2

Panel C. Reported industry-level opportunities *n* = 93. Respondents could select up to three options; therefore, percentages do not sum to 100%		
Reported opportunity	**n**	**% of firms**
Improved efficiency of teams and business models	39	41.9
Redistribution of routine tasks to AI, allowing employees to focus on strategic and creative work	30	32.3
Generation of new ideas and unconventional solutions	29	31.2
Advanced analysis of large datasets, identification of hidden patterns, and trend forecasting	28	30.1
Faster introduction of products and services to the market	24	25.8
Improved forecasting quality	15	16.1
Modeling complex processes, conducting virtual experiments, and testing hypotheses	13	14.0
Industry transformation and the emergence of new sources of value	12	12.9
Personalization of products, services, and processes	9	9.7
AI offers no opportunities for the industry	5	5.4
Other	2	2.2

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Table A3 (cont.). Managers' industry-level perceptions and assessments of AI

Panel D. Managerial assessments of AI-enabled innovation
Ratings ranged from 1 = strongly disagree to 5 = strongly agree. "Unable to answer" responses were excluded from the calculation of means, standard deviations, and medians. Agreement percentages were calculated among respondents providing substantive ratings; unable-to-answer percentages were calculated from the full sample (*n* = 93)

Statement	Valid n	Mean	SD	Median	Agree or strongly agree, %	Unable to answer, %
AI-generated ideas demonstrate a high degree of novelty and value	79	2.95	1.36	3	36.7	15.1
AI enables a more accurate understanding of customer needs and market trends	81	2.83	1.19	3	29.6	12.9
AI substantially reduces the time required to develop new products, services, or processes	82	3.35	1.31	4	51.2	11.8
AI helps reduce risks associated with innovation activities	76	3.00	1.24	3	31.6	18.3
The use of AI in developing new products, services, or processes is ethical	80	2.95	1.37	3	37.5	14.0