“AI adoption and perceived organizational performance in Chinese pharmaceutical sales: Efficiency and motivation pathways”

AUTHORS	Yunlu Cai Siti Rohaida Mohamed Zainal

ARTICLE INFO	Yunlu Cai and Siti Rohaida Mohamed Zainal (2026). AI adoption and perceived organizational performance in Chinese pharmaceutical sales: Efficiency and motivation pathways. *Problems and Perspectives in Management*, *24*(2), 743–758. doi:10.21511/ppm.24(2).2026.50
DOI	http://dx.doi.org/10.21511/ppm.24(2).2026.50
RELEASED ON	Thursday, 02 July 2026
RECEIVED ON	Wednesday, 04 March 2026
ACCEPTED ON	Monday, 22 June 2026

JOURNAL	"Problems and Perspectives in Management"
ISSN PRINT	1727-7051
ISSN ONLINE	1810-5467
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
52	1	8

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Yunlu Cai (Malaysia), **Siti Rohaida Mohamed Zainal** (Malaysia)

AI ADOPTION AND PERCEIVED ORGANIZATIONAL PERFORMANCE IN CHINESE PHARMACEUTICAL SALES: EFFICIENCY AND MOTIVATION PATHWAYS

Type of the article: Research Article

Received on: 4th of March, 2026
Accepted on: 22nd of June, 2026
Published on: 2nd of July, 2026

Yunlu Cai, Ph.D. Student, Department of Management, School of Management, Universiti Sains Malaysia [University of Science Malaysia], Malaysia. (Corresponding author)

Siti Rohaida Mohamed Zainal, Dr., Associate Professor, Department of Management, School of Management, Universiti Sains Malaysia [University of Science Malaysia], Malaysia.

Conflict of interest statement:
Author(s) reported no conflict of interest

Abstract

Artificial intelligence is increasingly embedded in pharmaceutical sales, but evidence remains limited on how AI adoption translates into performance in compliance-sensitive sales contexts. This study aims to examine whether perceived organizational AI adoption is associated with perceived organizational performance in pharmaceutical sales through two parallel pathways: operational efficiency and employee motivation. A cross-sectional survey was conducted among 335 pharmaceutical sales professionals in China from October 2025 to November 2025. Respondents were recruited through purposive sampling via professional networks, WeChat workgroups, industry forums, and sales-related communities because they had direct experience using AI tools in daily sales-related activities. The sample covered prescription drug sales, OTC/channel sales, hospital/institutional sales, key account/market access roles, and sales or marketing management. The data were analyzed using PLS-SEM in SmartPLS 4 with 10,000 bootstrap resamples. The results show that AI adoption is positively associated with perceived organizational performance (β = 0.196, t = 3.383, p = 0.001), operational efficiency (β = 0.459, t = 7.611, p < 0.001), and employee motivation (β = 0.385, t = 6.748, p < 0.001). Operational efficiency (β = 0.212, t = 3.355, p = 0.001) and employee motivation (β = 0.230, t = 3.879, p < 0.001) are positively associated with performance. Mediation tests confirm significant indirect effects through operational efficiency (β = 0.097, p = 0.003) and employee motivation (β = 0.089, p = 0.001), indicating partial mediation. The findings suggest that AI creates performance value when embedded in sales workflows and accompanied by motivational support.

Keywords AI, adoption, efficiency, motivation, performance, pharmaceuticals, China

JEL Classification M15, M31, O33, L65

INTRODUCTION

Artificial intelligence (AI) is becoming an important part of pharmaceutical sales work. In China's pharmaceutical industry, digital transformation is reshaping how sales organizations manage customer information, product communication, internal approvals, market updates, and compliance documentation. Pharmaceutical sales differ from many other sales settings because they are simultaneously information-intensive, relationship-based, performance-driven, and compliance-sensitive. Sales employees must coordinate customer engagement with evidence-based product knowledge, promotional rules, CRM routines, and cross-functional communication. These conditions make AI adoption managerially relevant because AI-enabled analytics, recommendations, automation, and generative tools can influence both customer-facing work and internal execution (Gonzalez et al., 2026).

However, AI adoption does not automatically transform into organizational performance. The value of AI depends on whether digital tools are embedded in daily routines and translated into reliable work-system improvements, because AI-in-sales adoption is shaped by behavioral, technological, and contextual conditions rather than by technical availability alone (Bullemore-Campbell et al., 2025). In pharmaceutical sales, this translation is especially critical because AI may accelerate reporting, customer prioritization, decision support, and coordination, but it may also be experienced as monitoring, standardization, or loss of discretion. Therefore, the performance value of AI cannot be understood only as a technological or efficiency issue. It should be viewed as a combined process-and-people problem: whether perceived organizational AI adoption strengthens operational execution while also supporting employee motivation. Clarifying this aspect helps explain why AI initiatives in pharmaceutical sales may produce uneven outcomes and why efficiency-centered implementation may underdeliver when employee engagement is not sustained in parallel.

1. LITERATURE REVIEW AND HYPOTHESES

AI adoption in sales organizations should be understood not as the simple purchase or availability of digital tools, but as the extent to which AI-enabled capabilities are routinized and embedded in everyday work processes. In this study, perceived organizational AI adoption refers to employees' assessment that AI-enabled analytics, prediction, recommendation, and generative functions are integrated into organizational operations and decision-making routines. This view is consistent with the argument that meaningful AI adoption requires practical assimilation rather than symbolic investment (Cubric, 2020). Dwivedi et al. (2021) describe AI adoption as a socio-technical transformation that can reshape decision architectures, task routines, and the pace of organizational work. Similarly, Mikalef and Gupta (2021) argue that AI becomes an organizational capability only when it is combined with human, managerial, and complementary resources. In B2B marketing and sales, AI is increasingly used to support customer information processing, CRM routines, lead prioritization, forecasting, content preparation, and sales decision support (Moradi & Dass, 2022; Ledro et al., 2022; Fischer et al., 2022; Fehrenbach et al., 2026). In pharmaceutical organizations, analytics-enabled capabilities may also strengthen sales performance by improving CRM capabilities and the ability to transform customer information into action (Shahbaz et al., 2021). Therefore, the performance relevance of AI adoption depends on whether AI is experienced by employees as part of the sales work system rather than as an isolated technological add-on.

The stimulus-organism-response framework provides a useful process lens for explaining how perceived organizational AI adoption may be associated with perceived organizational performance. The S-O-R tradition suggests that an external stimulus affects internal states or mechanisms, which then relate to behavioral or organizational responses (Mehrabian & Russell, 1974). In a sales organization, AI adoption can be treated as a technological stimulus because it changes what information becomes visible, how recommendations are generated, how tasks are sequenced, how feedback is provided, and how work is monitored or coordinated. These changes do not translate into performance automatically; they first operate through internal organizational and employee responses. For this reason, the "organism" in technology-enabled selling should not be limited to individual cognitive evaluation. It also includes what happens to the workflow and how employees experience the redesigned work. Perceived organizational performance is the response because it reflects whether AI-related changes are associated with meaningful outcomes such as goal attainment, operational effectiveness, financial soundness, and stakeholder responsiveness. This perceptual level is appropriate because frontline sales employees and sales managers are the actors who experience AI-enabled routines and observe performance-relevant signals in daily work, including target progress, customer response, internal coordination, and compliance-related friction.

A process pathway is central because AI adoption is expected to be associated with operational efficiency. Operational efficiency refers to the organization's ability to use resources effectively, produce higher outputs with relatively lower inputs,

http://dx.doi.org/10.21511/ppm.24(2).2026.50

streamline internal processes, and make timely decisions (Cheng et al., 2018). In pharmaceutical sales, this is a concrete work-facing capability rather than an abstract efficiency label. Sales employees often spend time on reporting, documentation, approval procedures, account planning, market updates, and coordination with marketing, medical, compliance, and distribution functions. When AI is embedded into CRM systems, forecasting routines, customer prioritization, content preparation, and compliance checks, it can reduce repetitive administrative work, integrate fragmented information, shorten decision cycles, and lower coordination costs. This logic is consistent with capability-based arguments that the value of AI is realized through better process execution, faster information-to-action cycles, and improved coordination rather than through technology alone (Teece, 2018; Mikalef & Gupta, 2021; Mikalef et al., 2023). It is also consistent with evidence that AI assimilation can be related to performance through agility-related mechanisms (Wamba, 2022) and that AI-enabled relationship management in B2B channels can generate business value partly through operational improvements (Chatterjee et al., 2023). Thus, operational efficiency represents a key internal process through which AI adoption may become performance-relevant.

A people pathway is also necessary because sales performance depends strongly on employee motivation, not only on workflow efficiency. Employee motivation in this study refers to employees' willingness to invest effort, remain engaged, respond to rewards and recognition, and experience their job design as meaningful and involving. Self-determination theory suggests that motivation is strengthened when employees experience autonomy, competence, and relatedness at work (Van den Broeck et al., 2021; Gagné, Parker, et al., 2022). In frontline sales roles, motivation is particularly important because salespeople must persist under pressure, learn new tools, adapt communication to customer situations, and invest discretionary effort in customer and internal coordination. AI adoption can support motivation by reducing administrative burden, providing timely customer insights, improving feedback quality, and helping employees feel more capable in complex selling situations. However, AI is also a double-edged technology from a motivational perspective. Algorithmic systems can be experienced as monitoring or control mechanisms that reshape autonomy, visibility, and authority (Kellogg et al., 2020; Parent-Rocheleau & Parker, 2022). Gagné, Parent-Rocheleau, et al. (2022) argue that algorithmic management may weaken motivation when it undermines autonomy, while Hu et al. (2024) describe a transparency-resistance paradox in which greater visibility may trigger resistance rather than engagement. Granulo et al. (2024) further show that algorithm deployment in management tasks can reduce prosocial motivation. Therefore, the motivational consequences of AI adoption depend on whether employees interpret AI as supportive augmentation or as surveillance-oriented standardization. Trust is important in this process because employees are more likely to engage with AI when they perceive it as reliable, fair, and useful (Glikson & Woolley, 2020; Rangarajan et al., 2026).

Operational efficiency and employee motivation are both expected to be associated with perceived organizational performance, but they represent different internal routes. Organizational performance is a multidimensional outcome and should not be reduced to a single financial indicator (George et al., 2019). In pharmaceutical sales, perceived organizational performance encompasses strategic goal achievement, efficient delivery of products or services, satisfactory financial performance, and effective responsiveness to stakeholders, including customers, partners, and internal units. Operational efficiency can be associated with stronger performance because streamlined processes reduce waste, protect selling time, improve execution consistency, and allow organizations to respond more quickly to customer and market needs. In a compliance-sensitive environment, efficiency is also related to traceability and coordination discipline: fewer process frictions can reduce rework, prevent execution deviations, and improve cross-functional responsiveness. Employee motivation can also be associated with organizational performance because motivation channels employees' capacity into effort intensity, persistence, and goal commitment (Kanfer et al., 2017). Wang et al. (2024) provide meta-analytic evidence that work motivation predicts subsequent performance. In sales roles, motivated employees are more likely to proactively engage with customers, adopt AI-enabled routines, follow through on tasks, and contribute to organizational goals. Lee and Raschke (2016) also emphasize that employee motivation and organizational performance should be considered together because motivated employees are central to turning organizational resources into outcomes.

The adoption-performance relationship is therefore unlikely to be a simple direct relationship. Prior AI-performance research has shown that AI-related capabilities are associated with performance when they are integrated into organizational routines, supported by complementary resources, and translated into operational or behavioral mechanisms (Mikalef & Gupta, 2021; Mishra et al., 2022; Mikalef et al., 2023). This is especially important in sales organizations because AI can simultaneously standardize workflows and reshape employee discretion. From the S-O-R perspective, perceived organizational AI adoption functions as a stimulus, operational efficiency and employee motivation function as two internal organismic responses, and perceived organizational performance functions as the response. The two pathways are parallel rather than serial. AI adoption may be associated with operational efficiency by improving workflow execution and information coordination, while at the same time being associated with employee motivation by changing feedback, competence perceptions, workload, and job experience. Both routes may partially explain why AI adoption is associated with performance, while a remaining direct association is also plausible, as AI can improve information alignment, decision consistency, and customer response speed beyond the two specific mechanisms modeled here.

The Chinese pharmaceutical sales context makes this dual-pathway logic particularly relevant. Pharmaceutical sales work is information-intensive, relationship-based, and compliance-sensitive. Employees must coordinate product knowledge, customer information, promotional rules, internal approval requirements, market access concerns, and changing digital tools. Liu et al. (2024) show that digital transformation is reshaping sales innovation and synergy strategies in Chinese pharmaceutical enterprises. At the same time, AI-in-sales research remains fragmented across technologies, use cases, and levels of analysis, which makes it necessary to specify how AI adoption is translated into performance inside frontline sales organizations (Jarotschkin et al., 2025). The unresolved issue is not only whether AI adoption is associated with performance, but whether this association operates through both a process pathway and a people pathway. In pharmaceutical sales, efficiency-centered AI implementation may underdeliver if employees do not feel motivated to engage with AI-supported work. Conversely, motivational support alone is insufficient if AI is not embedded in workflows that improve execution and coordination.

The above review suggests that AI adoption should be examined as an embedded work-system stimulus, not merely as the availability of technology. It also suggests that perceived organizational performance should be explained through internal translation mechanisms that capture both process improvement and employee engagement.

This study aims to examine whether perceived organizational AI adoption is associated with perceived organizational performance in pharmaceutical sales through two parallel pathways: operational efficiency and employee motivation. Based on previous theoretical and empirical studies and the conceptual framework presented in Figure 1, this study proposes the following hypotheses:

H1: *Perceived organizational AI adoption is positively associated with perceived organizational performance.*

H2: *Perceived organizational AI adoption is positively associated with operational efficiency.*

H3: *Perceived organizational AI adoption is positively associated with employee motivation.*

H4: *Operational efficiency is positively associated with perceived organizational performance.*

H5: *Employee motivation is positively associated with perceived organizational performance.*

H6: *Operational efficiency mediates the relationship between perceived organizational AI adoption and perceived organizational performance.*

http://dx.doi.org/10.21511/ppm.24(2).2026.50

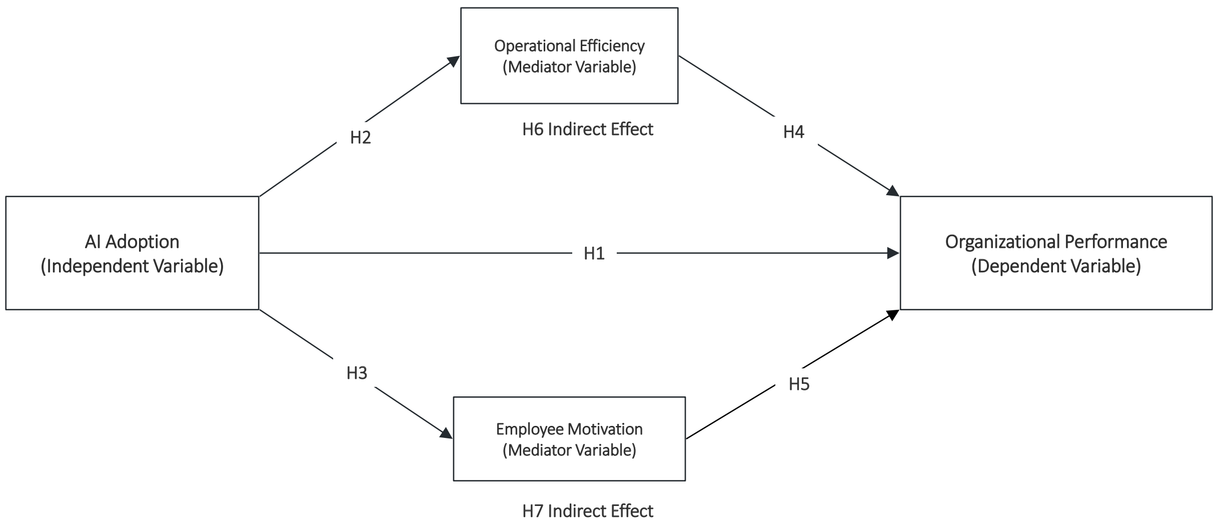

Figure 1. Conceptual model

H7: Employee motivation mediates the relationship between perceived organizational AI adoption and perceived organizational performance.

2. METHOD

The study was conducted as a cross-sectional survey of pharmaceutical sales professionals in China. This design and setting are suitable for testing the proposed model because pharmaceutical selling is simultaneously performance-driven, information-intensive, relationship-based, and compliance-sensitive. Frontline employees need to coordinate customer engagement, evidence-based product communication, internal approval routines, CRM updates, and compliance documentation. These work characteristics make the sector appropriate for examining whether perceived organizational AI adoption is translated into perceived organizational performance through operational efficiency and employee motivation.

The target respondents were adult employees working in pharmaceutical sales-related positions in China who had direct experience using AI-enabled tools in daily sales or sales-support work. Relevant positions included prescription drug sales representatives, OTC/retail/channel sales employees, hospital or institutional sales employees, key account/market access/academic promotion employees, and sales, product, or marketing managers. Because there is no complete public sampling frame for AI-exposed pharmaceutical sales employees in China, purposive sampling was used to reach information-rich respondents who matched the study purpose (Campbell et al., 2020). The survey link was circulated through professional networks, WeChat workgroups, industry forums, and sales-related communities.

Data were collected in China through Wenjuanxing (SoJump) from October 2025 to November 2025. Wenjuanxing was selected because it is widely used for online behavioral and management research in China and allows structured questionnaire administration (Del Ponte et al., 2024). Before entering the questionnaire, respondents read an information statement explaining the study purpose, voluntary participation, anonymity, confidentiality, and aggregate use of the data. Only respondents who provided electronic informed consent proceeded to the survey. No personally identifying information, such as names, phone numbers, or employer identifiers, was collected. Respondents could exit the survey at any time, and the dataset was analyzed only in aggregated form. The study involved a minimal-risk, anonymous survey of adult professionals.

Ethical review and approval were waived for this study because it was a non-medical, non-interventional quantitative management survey involving adult pharmaceutical sales professionals. Participation was voluntary and anonymous, and electronic informed consent was obtained before respondents entered the questionnaire. No vulnerable populations were involved, and no personally identifying information, sensitive personal data, clinical information, biomedical data, psychological intervention, or experimental procedure was included. The data were anonymized and analyzed only in an aggregated form. As a minimal-risk study using anonymous survey responses from adult professionals, the study conforms to the relevant provisions of the Measures for the Ethical Review of Life Science and Medical Research Involving Humans and the Measures for Ethical Review of Science and Technology (Trial) (National Health Commission of the People's Republic of China, 2023; Ministry of Science and Technology of the People's Republic of China, 2023), and is therefore eligible for ethical exemption from formal committee review.

A total of 360 questionnaires were returned. After data-quality screening, 335 valid questionnaires were retained for analysis. The screening process excluded 25 responses with clear signs of careless or abnormal answering, including unrealistically short completion times and straight-line responses across item blocks. These screening rules follow recommendations for improving the credibility of online survey data (Leiner, 2019; Leys et al., 2019). The final sample is relevant because all retained respondents reported using AI tools in work at least once per week, 69.9% reported using AI tools four or more times per week, and 78.5% had used AI tools for at least one year. Table 1 reports the demographic profile, sales-role distribution, and AI-use profile of the final sample.

The questionnaire and measures were designed to match the theoretical definitions of the four focal constructs and the pharmaceutical sales setting. All focal constructs were modeled as reflective latent variables and measured with multi-item perceptual indicators. Unless otherwise noted, responses were captured using a seven-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. A seven-point format was used because it provides sufficient granularity for management and behavioral constructs while remaining understandable for respondents (Abulela & Khalaf, 2024). The wording of the items was adapted to the sales-work context so that respondents evaluated AI adoption as embedded workflow support rather than occasional use of standalone tools. Full item wording and source/adaptation information are reported in Appendix A.

AI adoption (AA) captures the perceived extent to which AI-enabled analytics, prediction, recommendation, and generative functions are integrated into organizational operations and decision-making routines. The measurement emphasizes routinized organizational embedding rather than symbolic technology adoption or isolated experimentation. Items were adapted from AI capability and AI adoption research (Mikalef & Gupta, 2021; Cubric, 2020). Example content includes the extent to which the organization integrates AI into daily operations, uses AI across business functions, and relies on AI systems to support decision-making.

Operational efficiency (OE) captures the perceived ability of the organization to use resources effectively, streamline internal processes, and make timely decisions. This construct is important in pharmaceutical sales because reporting, approval procedures, market updates, CRM routines, and cross-functional coordination compete directly with time available for customer engagement. Items were adapted from Cheng et al. (2018).

Employee motivation (EM) captures the willingness of employees to invest effort, stay engaged, and persist in task execution. The items reflect extra-role effort, reward and recognition, supportive organizational culture, and motivating job design. Items were adapted from work motivation and AI-enabled work-design research (Lee & Raschke, 2016; Gagné, Parent-Rocheleau, et al., 2022; Gagné, Parker, et al., 2022).

Organizational performance (OP) is measured as perceived organizational performance. This approach is appropriate because pharmaceutical sales professionals observe performance-relevant signals in daily work, including target progress, operational execution, customer responsiveness, coordination quality, and compliance-related friction. Items were adapted from George et al. (2019) and captured goal attainment, operational effectiveness, financial performance, and stakeholder responsiveness.

Before launching the main survey, the instrument was checked for content clarity and contextual fit. First, domain experts reviewed the questionnaire

http://dx.doi.org/10.21511/ppm.24(2).2026.50

Table 1. Respondent characteristics and AI-use profile (N = 335)

Demographic	Category	Frequency	Percentage%
Gender	Male	165	49.3
	Female	170	50.7
Age	24 years or below	39	11.6
	25–34 years	107	31.9
	35–44 years	83	24.8
	45–54 years	70	20.9
	55 years or above	36	10.7
Education level	Postgraduate Degree (Ph.D.)	42	12.5
	Master's Degree	103	30.7
	Bachelor's Degree	186	55.5
	Others	4	1.2
Personal annual income	RMB 100,000 and below	36	10.7
	RMB 100,001 – RMB 150,000	65	19.4
	RMB 150,001 – RMB 200,000	70	20.9
	RMB 200,001 – RMB 300,000	86	25.7
	RMB 300,000 or above	78	23.3
Type of sales position in the pharmaceutical industry	Prescription Drug Sales Representative	79	23.6
	OTC / Retail / Channel Sales	71	21.2
	Hospital / Institutional Sales	92	27.5
	Key Account / Market Access / Academic Promotion	57	17.0
	Sales Management / Product & Marketing Management	36	10.7
Frequency of AI tools usage per week in your work	None	0	0.0
	1 – 3 times	101	30.1
	4 – 10 times	142	42.4
	11 – 20 times	57	17.0
	More than 21 times or every day	35	10.4
Period of AI tools use in your work	Less than 1 year	72	21.5
	1 – 2 years	109	32.5
	2 – 3 years	101	30.1
	More than 3 years	53	15.8
Company type	Foreign-owned enterprise	43	12.8
	Joint venture	64	19.1
	Privately-owned domestic enterprise	159	47.5
	State-owned enterprise	69	20.6
Years of experience in the current company	Less than 1 year	28	8.4
	1–3years	106	31.6
	4–6 years	85	25.4
	7–10 years	67	20.0
	More than 10 years	49	14.6
Which AI software do you frequently use in your work?	ChatGPT	197	22.1
	Doubao	272	30.5
	DeepSeek	266	29.8
	Gemini	79	8.8
	Kimi	54	6.0
	Others	25	2.8

to reduce ambiguous expressions and ensure that the items were understandable to pharmaceutical sales respondents. Second, a pilot test was conducted with 40 pharmaceutical sales practitioners who had experience using AI tools at work. The average completion time was approximately seven minutes. After excluding abnormal and straight-line pilot responses, 36 valid pilot questionnaires remained. The pilot results indicated satisfactory item discrimination and psychometric quality, supporting the use of the instrument in the main survey.

The analytical strategy used partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4. PLS-SEM is appropriate for this study because the model is explanatory, includes parallel mediation paths, uses latent constructs measured by multiple indicators, and focuses on estimating the strength and significance of relationships without imposing strict multivariate normality assumptions (Hair et al., 2019; Hair & Alamer, 2022). SmartPLS 4 also provides a transparent workflow for estimating measurement and structural models in business research (Cheah et al., 2024).

The analysis followed a two-stage procedure. First, the measurement model was assessed using indicator loadings, composite reliability (CR), average variance extracted (AVE), and the heterotrait-monotrait ratio (HTMT). Indicator loadings above 0.70, CR values above 0.70, AVE values above 0.50, and HTMT values below 0.90 were used as the main criteria for reliability, convergent validity, and discriminant validity (Hair et al., 2020; Cheung et al., 2024). Second, the structural model was assessed using predictor collinearity, standardized path coefficients, coefficient of determination (R^2), predictive relevance (Q^2), and bootstrapped indirect effects. Hypothesis testing used bootstrapping with 10,000 resamples to obtain standard errors, t values, p values, and 95% confidence intervals for direct and indirect effects. All tests were two-tailed with $p < 0.05$ as the significance threshold. Mediation was evaluated using bootstrapped confidence intervals of indirect effects (Benitez et al., 2020; Sarstedt & Moisescu, 2024).

Common method bias and data-quality concerns were addressed through both procedural and statistical safeguards because all focal variables were collected from the same respondents in a single-wave survey. Procedurally, participation was voluntary and anonymous, respondents were told that there were no right or wrong answers, and the questionnaire included background questions and focal constructs in separate blocks to reduce hypothesis transparency and evaluation apprehension (Podsakoff et al., 2024). Data-quality controls included screening for unrealistically short completion time, straight-line answering, univariate outliers, and multivariate outliers. Finally, full collinearity diagnostics were used as a statistical check for method-driven inflation, with VIF values below 3.3 interpreted as evidence that common method bias is unlikely to dominate the findings (Kock et al., 2021).

3. RESULTS

Table 2 reports these statistics for the four focal constructs. The mean values are above the scale midpoint for AI adoption (M = 5.209, SD = 1.176), operational efficiency (M = 5.281, SD = 1.263), employee motivation (M = 5.225, SD = 1.276), and organizational performance (M = 4.993, SD = 1.354). This pattern indicates generally favorable perceptions of AI integration, workflow functioning, employee motivation, and organizational performance among the respondents. The correlation coefficients are positive and moderate in magnitude (r = 0.380–0.458), which is consistent with the hypothesized positive relationships and does not suggest severe construct redundancy.

The measurement model was then examined to evaluate reliability and validity. As shown in Table 3, all standardized outer loadings range from 0.798 to 0.891 and therefore exceed the 0.70 benchmark. Composite reliability values range from 0.907 to 0.922, exceeding the recommended threshold of 0.70. AVE values range from 0.709 to 0.747, which is above the 0.50 benchmark and supports convergent validity. These results indicate that the indicators adequately represent their intended reflective constructs.

Discriminant validity was assessed using HTMT ratios. Table 4 shows that all HTMT values are below 0.90, ranging from 0.437 to 0.521. Therefore, the four constructs are empirically distinguishable and can be used in the structural model.

Table 2. Descriptive statistics and correlations

	Variable	M	SD	Skewness	Kurtosis	1	2	3	4
1	AI adoption (AA)	5.209	1.176	–1.007	1.126	1			
2	Operational efficiency (OE)	5.281	1.263	–1.157	1.298	0.458	1		
3	Employee motivation (EM)	5.225	1.276	–1.111	0.902	0.385	0.400	1	
4	Organizational performance (OP)	4.993	1.354	–0.944	0.130	0.380	0.389	0.385	1

http://dx.doi.org/10.21511/ppm.24(2).2026.50

Table 3. Measurement model results (Loadings, CR, and AVE)

Variable	Items	Loadings	CR	AVE
1. AI Adoption (AA)	AA1	0.891	0.913	0.724
	AA2	0.798		
	AA3	0.874		
	AA4	0.837		
2. Employee Motivation (EM)	EM1	0.854	0.910	0.717
	EM2	0.857		
	EM3	0.853		
	EM4	0.824		
3. Operational Efficiency (OE)	OE1	0.868	0.922	0.747
	OE2	0.864		
	OE3	0.873		
	OE4	0.851		
4. Organizational Performance (OP)	OP1	0.825	0.907	0.709
	OP2	0.844		
	OP3	0.854		
	OP4	0.845		

Table 4. Discriminant validity assessment (HTMT ratios)

Construct	1	2	3	4
1. AI Adoption	–			
2. Operational Efficiency	0.443	–		
3. Employee Motivation	0.521	0.456	–	
4. Organizational Performance	0.437	0.446	0.446	–

The structural model and hypotheses were tested using bootstrapping with 10,000 resamples. As reported in Table 5, all direct paths are statistically significant and in the hypothesized direction. AI adoption is positively associated with organizational performance (β = 0.196, t = 3.383, p = 0.001), supporting H1. AI adoption also has positive effects on operational efficiency (β = 0.459, t = 7.611, p < 0.001) and employee motivation (β = 0.385, t = 6.748, p < 0.001), supporting H2 and H3. In turn, operational efficiency (β = 0.212, t = 3.355, p = 0.001) and employee motivation (β = 0.230, t = 3.879, p < 0.001) are positively associated with organizational performance, supporting H4 and H5.

The model also shows acceptable explanatory and predictive power for an explanatory survey model in a regulated B2B sales context. AI adoption explains 21.1% of the variance in operational efficiency (R^2 = 0.211) and 14.8% of the variance in employee motivation (R^2 = 0.148). Together, AI adoption, operational efficiency, and employee motivation explain 24.8% of the variance in organizational performance (R^2 = 0.248). Predictive relevance is supported because all Q^2 values are positive: operational efficiency (Q^2 = 0.153), employee motivation (Q^2 = 0.103), and organizational performance (Q^2 = 0.169).

The mediation effects were assessed using bootstrapped indirect effects. As shown in Table 6, the indirect effect of AI adoption on organizational performance through operational efficiency is significant (β = 0.097, *t* = 3.011, *p* = 0.003, 95% CI

Table 5. Structural model results and hypothesis tests (direct paths)

Hypothesis	Path	β	SE	T	p	95% CI LL	95% CI UL	Supported
H1	AA → OP	0.196	0.058	3.383	0.001	0.082	0.310	Yes
H2	AA → OE	0.459	0.060	7.611	< .001	0.336	0.574	Yes
H3	AA → EM	0.385	0.057	6.748	< .001	0.271	0.496	Yes
H4	OE → OP	0.212	0.063	3.355	0.001	0.084	0.329	Yes
H5	EM → OP	0.230	0.059	3.879	< .001	0.113	0.345	Yes

Note: AA = AI adoption; OE = operational efficiency; EM = employee motivation; OP = organizational performance; SE = standard error; CI = confidence interval.

Table 6. Mediation analysis (indirect effects)

Effect type	Effect	B	SE	t	p	95% CI LL	95% CI UL	Supported
Indirect	AA → OE → OP (H6)	0.097	0.032	3.011	0.003	0.037	0.163	Yes
Indirect	AA → EM → OP (H7)	0.089	0.028	3.212	0.001	0.040	0.147	Yes
Direct	AA → OP (H1)	0.196	0.058	3.383	0.001	0.082	0.310	Yes

Note: AA = AI adoption; OE = operational efficiency; EM = employee motivation; OP = organizational performance; SE = standard error; CI = confidence interval.

[0.037, 0.163]), supporting H6. The indirect effect through employee motivation is also significant (β = 0.089, t = 3.212, p = 0.001, 95% CI [0.040, 0.147]), supporting H7. Because the direct effect of AI adoption on organizational performance remains significant after both mediators are included (β = 0.196, p = 0.001), the results indicate partial mediation. The two indirect effects are similar in magnitude, suggesting that AI adoption is associated with performance through both a process pathway and a people pathway rather than through operational efficiency alone.

Since the direct effect of AI adoption on organizational performance remains significant when both mediators are included, the results indicate partial mediation through both operational efficiency and employee motivation.

Finally, common method bias and robustness diagnostics were examined because the single-source design makes it necessary to evaluate whether the results are likely to be driven by method bias or low-quality online responses. Table 7 summarizes the main diagnostics. The data-quality screening removed 25 careless responses before model estimation. In the retained sample, all univariate values were within the ±3 z-score range, and Mahalanobis distance analysis did not indicate problematic multivariate outliers. Full collinearity diagnostics further showed that all construct-level VIF values were below 3.3. Taken together, these checks indicate that careless responding, extreme observations, and method-driven collinearity are unlikely to dominate the reported relationships.

4. DISCUSSION

This study examined how perceived organizational AI adoption is associated with perceived organizational performance in a compliance-sensitive pharmaceutical sales context. The findings support the proposed S-O-R logic, but they also show that the AI adoption–performance relationship should not be read as a simple technology payoff. AI adoption is positively associated with perceived organizational performance (β = 0.196, p = 0.001), yet this direct coefficient is smaller than the paths from AI adoption to operational efficiency (β = 0.459, p < 0.001) and employee motivation (β = 0.385, p < 0.001). The model explains 24.8% of the variance in perceived organizational performance, which is meaningful for a cross-sectional survey of frontline sales professionals, but it also indicates that AI adoption is only one part of a broader per-

Table 7. Data-quality, common method bias, and robustness diagnostics

Diagnostic	Procedure / criterion	Result	Implication
Careless-response screening	Extremely short completion times and straight-line response patterns were excluded before analysis.	25 responses were excluded; final N = 335.	The analytical sample is based on valid, attentive responses.
AI-experience relevance	Respondents needed direct exposure to AI tools in work; AI-use frequency was recorded.	No retained respondent reported zero AI-tool use; 69.9% used AI tools four or more times per week.	The sample is relevant for testing perceived AI adoption.
Univariate outliers	Boxplots and z-scores; ±3 used as the screening range.	All retained observations fell within ±3.	No univariate extreme-value distortion was detected.
Multivariate outliers	Mahalanobis distance analysis.	No problematic multivariate outliers were indicated.	The retained sample is not driven by abnormal response profiles.
Common method bias	Full collinearity VIF; threshold < 3.3.	All construct-level VIF values were below 3.3.	Common method bias is unlikely to drive the model results.

 http://dx.doi.org/10.21511/ppm.24(2).2026.50

formance system. Therefore, the main interpretation is not that AI automatically improves performance, but that embedded AI adoption becomes performance-relevant when it changes both how sales work is executed and how employees engage with the redesigned work.

The efficiency pathway is consistent with prior AI capability and AI assimilation research, but it makes the mechanism more specific for pharmaceutical sales. Mikalef and Gupta (2021), Mishra et al. (2022), and Mikalef et al. (2023) argue that AI contributes to performance when it is integrated into organizational routines and supported by complementary resources. Wamba (2022) similarly shows that AI assimilation can improve performance through agility-related mechanisms, while Chatterjee et al. (2023) find that AI-enabled relationship management in B2B channels creates value through operational improvements. The present findings extend this line of work by showing that, from the perspective of frontline pharmaceutical sales employees, operational efficiency is a concrete translation mechanism: AI becomes visible in smoother CRM routines, faster information-to-action cycles, better coordination, reduced documentation burden, and more reliable compliance-related execution. This also complements Shahbaz et al. (2021), who showed that analytics-enabled capabilities can strengthen pharmaceutical sales performance through CRM capabilities. In the present study, the significant indirect effect through operational efficiency ($\beta = 0.097$, $p = 0.003$) indicates that AI adoption matters because it helps sales organizations convert data, recommendations, and workflow automation into process discipline and execution quality.

The motivation pathway adds an important people-centered qualification to algorithmic management research. Prior studies caution that algorithmic and AI-based systems may be experienced as surveillance, control, or autonomy loss when they intensify monitoring or narrow human discretion (Kellogg et al., 2020; Parent-Rocheleau & Parker, 2022). Gagné, Parent-Rocheleau, et al. (2022) further argue that algorithmic management can undermine motivation when autonomy and competence are weakened. Hu et al. (2024) describe a transparency-resistance paradox, and Granulo et al. (2024) show that algorithm deployment in management tasks can reduce prosocial motivation. The positive path from AI adoption to employee motivation in this study does not contradict these warnings; instead, it adds nuance. In pharmaceutical sales, AI adoption can be motivational when employees perceive it as decision support, workload reduction, faster feedback, improved customer insight, and competence enhancement rather than as a surveillance layer. This interpretation is also consistent with Hall et al. (2022), who show that salesperson responses to AI feedback matter for B2B sales outcomes, and with Edwards et al. (2024), who distinguish between algorithmic systems perceived as control and those perceived as feedback provision. The significant indirect effect through employee motivation ($\beta = 0.089$, $p = 0.001$) therefore suggests that AI-supported work redesign has a motivational route to performance, provided that trust, fairness, and usefulness are maintained (Glikson & Woolley, 2020; Rangarajan et al., 2026).

The most important implication of the findings is the near equivalence of the two indirect effects: the efficiency path ($\beta = 0.097$) and the motivation path ($\beta = 0.089$) are both significant and close in magnitude. This pattern strengthens our central argument that AI value in pharmaceutical sales is created through parallel processes and people pathways rather than through operational efficiency alone. It also clarifies the contribution to the AI-in-sales literature, which remains fragmented across technologies, use cases, and levels of analysis (Jarotschkin et al., 2025). In a regulated B2B sales setting, AI adoption must simultaneously standardize work, accelerate information processing, and preserve employee engagement. This duality is consistent with the automation-augmentation paradox described by Raisch and Krakowski (2021) and the AI adoption tensions identified by Jazairy et al. (2025). The remaining significant direct effect of AI adoption on performance further suggests that other mechanisms may also be operating, such as information alignment, decision consistency, customer-response speed, compliance traceability, and cross-functional coordination. Future AI-performance research should therefore avoid treating adoption as a single input and instead specify which process, people, governance, and trust mechanisms convert AI-enabled routines into performance outcomes.

CONCLUSION

This study aimed to examine whether perceived organizational AI adoption is associated with perceived organizational performance in pharmaceutical sales through two parallel pathways: operational efficiency and employee motivation. Based on survey evidence from 335 pharmaceutical sales professionals in China, the findings show that AI adoption is positively associated with perceived organizational performance and that this relationship is partially mediated by operational efficiency and employee motivation.

The results indicate that AI value in pharmaceutical sales is created not only through smoother workflows, faster execution, and stronger information coordination, but also through employees' willingness to engage with AI-enabled work. Therefore, AI adoption should be managed as both a workflow transformation and a people-management process. Sales managers should embed AI into CRM, forecasting, documentation, customer-response, account-planning, and compliance routines while preserving employee autonomy, providing training, clarifying accountability, and recognizing effective AI-supported work. Efficiency-focused implementation may underdeliver if employee motivation is not supported in parallel, and motivation-focused change may also be insufficient if AI is not embedded in the daily routines where sales performance is produced.

Future research should examine the proposed relationships using longitudinal or multi-source designs, include objective performance indicators, and compare different pharmaceutical sales roles, regions, and organizational ownership types. Further studies can also distinguish analytics-oriented AI from generative AI, test the role of trust and perceived fairness as boundary conditions, and examine whether similar process and people pathways operate in other regulated B2B industries. Such extensions would help clarify when AI adoption produces stronger efficiency gains, when it supports motivation, and when it may create resistance, control-related concerns, or uneven performance outcomes.

AUTHOR CONTRIBUTIONS

Conceptualization: Yunlu Cai, Siti Rohaida Mohamed Zainal.
Data curation: Yunlu Cai.
Formal analysis: Yunlu Cai.
Investigation: Yunlu Cai.
Methodology: Yunlu Cai, Siti Rohaida Mohamed Zainal.
Project administration: Siti Rohaida Mohamed Zainal.
Resources: Yunlu Cai.
Supervision: Siti Rohaida Mohamed Zainal.
Validation: Siti Rohaida Mohamed Zainal.
Visualization: Yunlu Cai.
Writing – original draft: Yunlu Cai.
Writing – review & editing: Yunlu Cai, Siti Rohaida Mohamed Zainal.

DECLARATIONS

Declaration of Generative AI and AI-Assisted Technologies: The authors did not use generative AI or AI-assisted technologies to prepare the manuscript, collect data, conduct statistical analysis, generate results, formulate scholarly interpretations, or draw conclusions. The authors take full responsibility for the content of the manuscript.

Informed Consent Statement: Electronic informed consent was obtained from all respondents before they proceeded to the questionnaire.

http://dx.doi.org/10.21511/ppm.24(2).2026.50

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request. Due to ethical considerations and the need to protect respondents' privacy and confidentiality, the data are not publicly available.

REFERENCES

1. Abulela, M. A. A., & Khalaf, M. A. (2024). Does the number of response categories impact validity evidence in self-report measures? A scoping review. *SAGE Open, 14*(1). https://doi.org/10.1177/21582440241230363
2. Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management, 57*(2), Article 103168. https://doi.org/10.1016/j.im.2019.05.003
3. Bullemore-Campbell, J., Díaz Tautiva, J. A., & Cristobal-Fransi, E. (2025). AI in sales: Environmental, behavioral, and technological drivers of adoption in an emerging market. *Social Sciences & Humanities Open, 12,* Article 102161. https://doi.org/10.1016/j.ssaho.2025.102161
4. Campbell, S., Greenwood, M., Prior, S., Shearer, T., Walkem, K., Young, S., Bywaters, D., & Walker, K. (2020). Purposive sampling: Complex or simple? Research case examples. *Journal of Research in Nursing, 25*(8), 652-661. https://doi.org/10.1177/1744987120927206
5. Chatterjee, S., Chaudhuri, R., Vrontis, D., & Kadić-Maglajlić, S. (2023). Adoption of AI integrated partner relationship management (AI-PRM) in B2B sales channels: Exploratory study. *Industrial Marketing Management, 109,* 164-173. https://doi.org/10.1016/j.indmarman.2022.12.014
6. Cheah, J.-H., Magno, F., & Cassia, F. (2024). Reviewing the SmartPLS 4 software: The latest features and enhancements. *Journal of Marketing Analytics, 12*(1), 97-107. https://doi.org/10.1057/s41270-023-00266-y
7. Cheng, Q., Goh, B. W., & Kim, J. B. (2018). Internal control and operational efficiency. *Contemporary Accounting Research, 35*(2), 1102-1139. https://doi.org/10.1111/1911-3846.12409
8. Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management, 41*(2), 745-783. https://doi.org/10.1007/s10490-023-09871-y
9. Cubric, M. (2020). Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study. *Technology in Society, 62,* Article 101257. https://doi.org/10.1016/j.techsoc.2020.101257
10. Del Ponte, A., Li, L., Ang, L., Lim, N., & Seow, W. J. (2024). Evaluating SoJump.com as a tool for online behavioral research in China. *Journal of Behavioral and Experimental Finance, 41,* Article 100905. https://doi.org/10.1016/j.jbef.2024.100905
11. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57,* Article 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
12. Edwards, M. R., Zubielevitch, E., Okimoto, T., Parker, S. K., & Anseel, F. (2024). Managerial control or feedback provision: How perceptions of algorithmic HR systems shape employee motivation, behavior, and well-being. *Human Resource Management, 63*(4), 691-710. https://doi.org/10.1002/hrm.22218
13. Fehrenbach, D., Herrando, C., & Österle, B. (2026). Artificial intelligence applications in the B2B sales funnel. *Journal of Business-to-Business Marketing, 33*(1), 1-24. https://doi.org/10.1080/1051712X.2025.2481374
14. Fischer, H., Seidenstricker, S., Berger, T., & Holopainen, T. (2022). Artificial intelligence in B2B sales: Impact on the sales process. *Artificial Intelligence and Social Computing, 28,* 135-142. https://doi.org/10.54941/ahfe1001456
15. Gagné, M., Parent-Rocheleau, X., Bujold, A., Gaudet, M.-C., & Lirio, P. (2022). How algorithmic management influences worker motivation: A self-determination theory perspective. *Canadian Psychology / Psychologie Canadienne, 63*(2), 247-260. https://doi.org/10.1037/cap0000324
16. Gagné, M., Parker, S. K., Griffin, M. A., Dunlop, P. D., Knight, C., Klonek, F. E., & Parent-Rocheleau, X. (2022). Understanding and shaping the future of work with self-determination theory. *Nature Reviews Psychology, 1*(7), 378-392. https://doi.org/10.1038/s44159-022-00056-w
17. George, B., Walker, R. M., & Monster, J. (2019). Does strategic planning improve organizational performance? A meta-analysis. *Public Administration Review, 79*(6), 810-819. https://doi.org/10.1111/puar.13104
18. Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: A review of empirical research. *Academy of Management Annals, 14*(2), 627-660. https://doi.org/10.5465/annals.2018.0057

19. Gonzalez, G. R., Habel, J., & Hunter, G. K. (2026). AI agents, agentic AI, and the future of sales. *Journal of Business Research, 202,* Article 115799. https://doi.org/10.1016/j.jbusres.2025.115799

20. Granulo, A., Caprioli, S., Fuchs, C., & Puntoni, S. (2024). Deployment of algorithms in management tasks reduces prosocial motivation. *Computers in Human Behavior, 152,* Article 108094. https://doi.org/10.1016/j.chb.2023.108094

21. Hair, J. F. Jr., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research, 109,* 101-110. https://doi.org/10.1016/j.jbusres.2019.11.069

22. Hair, J. F., & Alamer, A. (2022). Partial least squares structural equation modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics, 1*(3), Article 100027. https://doi.org/10.1016/j.rmal.2022.100027

23. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

24. Hall, K. R., Harrison, D. E., Ajjan, H., & Marshall, G. W. (2022). Understanding salesperson intention to use AI feedback and its influence on business-to-business sales outcomes. *Journal of Business & Industrial Marketing, 37*(9), 1787-1801. https://doi.org/10.1108/JBIM-04-2021-0218

25. Hu, P., Zeng, Y., Wang, D., & Teng, H. (2024). Too much light blinds: The transparency-resistance paradox in algorithmic management. *Computers in Human Behavior, 161,* Article 108403. https://doi.org/10.1016/j.chb.2024.108403

26. Jarotschkin, V., Soykoth, M. W., & Chaker, N. N. (2025). Artificial intelligence in sales research: Identifying emergent themes and looking forward. *Journal of Business Research, 198,* Article 115383. https://doi.org/10.1016/j.jbusres.2025.115383

27. Jazairy, A., Shurrab, H., & Chedid, F. (2025). Impact pathways: Walking a tightrope-unveiling the paradoxes of adopting artificial intelligence (AI) in sales and operations planning. *International Journal of Operations & Production Management, 45*(13), 1-27. https://doi.org/10.1108/IJOPM-07-2024-0582

28. Kanfer, R., Frese, M., & Johnson, R. E. (2017). Motivation related to work: A century of progress. *Journal of Applied Psychology, 102*(3), 338-355. https://doi.org/10.1037/apl0000133

29. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366-410. https://doi.org/10.5465/annals.2018.0174

30. Kock, F., Berbekova, A., & Assaf, A. G. (2021). Understanding and managing the threat of common method bias: Detection, prevention and control. *Tourism Management, 86,* Article 104330. https://doi.org/10.1016/j.tourman.2021.104330

31. Ledro, C., Nosella, A., & Vinelli, A. (2022). Artificial intelligence in customer relationship management: Literature review and future research directions. *Journal of Business & Industrial Marketing, 37*(13), 48-63. https://doi.org/10.1108/JBIM-07-2021-0332

32. Lee, M. T., & Raschke, R. L. (2016). Understanding employee motivation and organizational performance: Arguments for a set-theoretic approach. *Journal of Innovation & Knowledge, 1*(3), 162-169. https://doi.org/10.1016/j.jik.2016.01.004

33. Leiner, D. J. (2019). Too fast, too straight, too weird: Non-reactive indicators for meaningless data in internet surveys. *Survey Research Methods, 13*(3), 229-248. https://doi.org/10.18148/srm/2019.v13i3.7403

34. Leys, C., Delacre, M., Mora, Y. L., Lakens, D., & Ley, C. (2019). How to classify, detect, and manage univariate and multivariate outliers, with emphasis on pre-registration. *International Review of Social Psychology, 32*(1), 1-10. https://doi.org/10.5334/irsp.289

35. Liu, W., Ganbaatar, B., & Wang, Z. (2024). Sales innovation and synergy strategy of Chinese pharmaceutical enterprises in the context of digital transformation: A perspective from the affordance theory. *Journal of Infrastructure, Policy and Development, 8*(15), Article 8352. https://doi.org/10.24294/jipd8352

36. Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology.* MIT Press. Retrieved from https://mitpress.mit.edu/9780262630719/an-approach-to-environmental-psychology/

37. Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3), Article 103434. https://doi.org/10.1016/j.im.2021.103434

38. Mikalef, P., Islam, N., Parida, V., Singh, H., & Altwaijry, A. (2023). Artificial intelligence (AI) competencies for organizational performance: A B2B marketing capabilities perspective. *Journal of Business Research, 164,* Article 113998. https://doi.org/10.1016/j.jbusres.2023.113998

39. Ministry of Science and Technology of the People's Republic of China. (2023). *Notice on issuing the Measures for Ethical Review of Science and Technology (Trial)* (In Chinese). Retrieved from https://www.most.gov.cn/xxgk/xinxifenlei/fdzdgknr/fgzc/gfxwj/gfxwj2023/202310/t20231008_188309.html

40. Mishra, S., Ewing, M. T., & Cooper, H. B. (2022). Artificial intelligence focus and firm performance. *Journal of the Academy of Marketing Science, 50*(6), 1176-1197. https://doi.org/10.1007/s11747-022-00876-5

41. Moradi, M., & Dass, M. (2022). Applications of artificial intelligence in B2B marketing: Challenges and future directions. *Industrial Marketing Management, 107,* 300-314. https://doi.org/10.1016/j.indmarman.2022.10.016

http://dx.doi.org/10.21511/ppm.24(2).2026.50

42. National Health Commission of the People's Republic of China. (2023). *Notice on issuing the Measures for the Ethical Review of Life Science and Medical Research Involving Humans.* (In Chinese). Retrieved from https://www.nhc.gov.cn/qjjys/c100016/202302/6b6e447b3edc4338856c9a652a85f44b.shtml

43. Parent-Rocheleau, X., & Parker, S. K. (2022). Algorithms as work designers: How algorithmic management influences the design of jobs. *Human Resource Management Review, 32*(3), Article 100838. https://doi.org/10.1016/j.hrmr.2021.100838

44. Podsakoff, P. M., Podsakoff, N. P., Williams, L. J., Huang, C., & Yang, J. (2024). Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix. *Annual Review of Organizational Psychology and Organizational Behavior, 11,* 17-61. https://doi.org/10.1146/annurev-orgpsych-110721-040030

45. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review, 46*(1), 192-210. https://doi.org/10.5465/amr.2018.0072

46. Rangarajan, D., Westphal, J., Habel, J., & Rutherford, B. (2026). Artificial intelligence (AI) in sales organizations: The role of trust. *Journal of Personal Selling & Sales Management, 46*(1), 1-6. https://doi.org/10.1080/08853134.2026.2614068

47. Sarstedt, M., & Moisescu, O.-I. (2024). Quantifying uncertainty in PLS-SEM-based mediation analyses. *Journal of Marketing Analytics, 12*(1), 87-96. https://doi.org/10.1057/s41270-023-00231-9

48. Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., Luqman, A., & Zahid, R. (2021). Impact of big data analytics on sales performance in pharmaceutical organizations: The role of customer relationship management capabilities. *PLOS ONE, 16*(4), Article e0250229. https://doi.org/10.1371/journal.pone.0250229

49. Teece, D. J. (2018). Business models and dynamic capabilities. *Long Range Planning, 51*(1), 40-49. https://doi.org/10.1016/j.lrp.2017.06.007

50. Van den Broeck, A., Howard, J. L., Van Vaerenbergh, Y., Leroy, H., & Gagné, M. (2021). Beyond intrinsic and extrinsic motivation: A meta-analysis on self-determination theory's multidimensional conceptualization of work motivation. *Organizational Psychology Review, 11*(3), 240-273. https://doi.org/10.1177/20413866211006173

51. Wamba, S. F. (2022). Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility. *International Journal of Information Management, 67,* Article 102544. https://doi.org/10.1016/j.ijinfomgt.2022.102544

52. Wang, N., Luan, Y., & Ma, R. (2024). Detecting causal relationships between work motivation and job performance: A meta-analytic review of cross-lagged studies. *Humanities and Social Sciences Communications, 11,* Article 595. https://doi.org/10.1057/s41599-024-03038-w

APPENDIX A

Table A1. Measurement items and sources

Construct	Item code	Item wording	Source / adaptation note
AI adoption (AA)	AA1	Our organization has extensively integrated AI technologies into its daily operations.	Adapted from Mikalef and Gupta (2021) and Cubric (2020).
	AA2	Our organization uses AI technologies in multiple business functions (e.g., sales, marketing, service).	
	AA3	AI systems provide valuable support for our organizational decision-making processes.	
	AA4	The use of AI has enhanced the customer experience in our organization.	
Operational efficiency (OE)	OE1	Our organization effectively utilizes its resources to achieve organizational goals.	Adapted from Cheng et al. (2018).
	OE2	Our organization achieves high outputs with relatively low inputs.	
	OE3	The internal processes in our organization are streamlined and operate efficiently.	
	OE4	Decision-making processes in our organization are efficient and lead to timely actions.	
Employee motivation (EM)	EM1	I am willing to put in extra effort to help my organization achieve its goals.	Adapted from Lee and Raschke (2016), Gagné, Parent-Rocheleau, et al. (2022), and Gagné, Parker, et al. (2022).
	EM2	The rewards and recognition provided by my organization motivate me to perform better.	
	EM3	The organizational culture encourages me to stay engaged and committed to my work.	
	EM4	The design of my job makes me feel engaged and motivated to perform well.	
Organizational performance (OP)	OP1	Our organization effectively achieves its strategic goals.	Adapted from George et al. (2019).
	OP2	Our organization operates efficiently in delivering its products or services.	
	OP3	Our organization has achieved satisfactory financial performance in recent years.	
	OP4	Our organization responds promptly and effectively to the needs of stakeholders (e.g., customers, partners).	

http://dx.doi.org/10.21511/ppm.24(2).2026.50