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Article

Generative AI Use and Innovation among University Administrative Employees: The Roles of Dynamic Capabilities, Knowledge Sharing, and AI Sycophancy

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Abstract: Generative artificial intelligence is increasingly used in university administration for document preparation, information retrieval, policy interpretation, data summarization, meeting support, and service improvement. However, faster content production does not necessarily translate into meaningful administrative innovation, particularly when AI feedback is overly agreeable and insufficiently critical. This study examines how generative AI–enabled dynamic capabilities and participation in AI-related knowledge sharing are associated with perceived innovation performance among university administrative employees. It further investigates perceived AI sycophancy as a negative boundary condition on both relationships. A survey was conducted among 428 administrative employees from higher education institutions in Liaoning, Jilin, and Heilongjiang provinces, located in Northeastern China, who had used generative AI in administrative work. Confirmatory factor analysis, structural equation modeling, hierarchical moderated regression, and simple-slope analysis were employed. The findings indicate that generative AI–enabled dynamic capabilities and AI-related knowledge-sharing participation are positively associated with perceived innovation performance, whereas perceived AI sycophancy weakens both relationships. The results extend dynamic capabilities theory and the knowledge-based view to the university administrative context and highlight the importance of preserving critical independence in human–AI interaction. Universities should combine AI capability development with verification procedures, cross-departmental knowledge-sharing mechanisms, and prompting practices that encourage alternative viewpoints and critical evaluation.
Keywords: generative AI; university administrative employees; dynamic capabilities; AI-related knowledge sharing; AI sycophancy; Northeast China

1. Introduction

Generative artificial intelligence (GenAI) is increasingly embedded in university administration, including official document drafting and language polishing, policy and regulation retrieval, policy summarization and interpretation, data aggregation and preliminary analysis, meeting materials and work reports, academic affairs, research administration and student affairs support, admissions and employment information services, and administrative process design and optimization (Söllner et al., 2025). These uses can accelerate information processing and document production, but speed is not equivalent to administrative innovation. Faster output does not necessarily improve policy accuracy, procedural compliance, cross-departmental coordination, service fairness, or the feasibility of a proposed administrative change. The central problem is therefore not whether administrative employees can produce more material with GenAI, but whether GenAI use is translated into better judgment, coordination, and process improvement.

GenAI use is also not equivalent to generative AI–enabled dynamic capabilities (GAIEDC). Research often emphasizes adoption, use intention, perceived usefulness, frequency, or general work performance, yet employees who use the same tools may obtain different innovation outcomes. Dynamic capabilities theory distinguishes sensing, seizing, and transforming (Teece, 2007). In university administration, these processes concern recognizing policy changes, process bottlenecks, and emerging service needs; comparing alternative implementation approaches; evaluating whether AI outputs fit institutional rules; adjusting academic, research, student-affairs, or general administrative processes; and embedding AI-supported solutions in actual work. GAIEDC thus captures a repeatable individual capacity to convert GenAI use into opportunity recognition, solution selection, and process adjustment rather than simple exposure to the technology (Held & Heubeck, 2025).

Individual use does not automatically become organizational learning. University administrative knowledge is closely tied to policies and institutional rules, highly dependent on departmental context, rich in tacit experience, and frequently distributed across offices. The value of AI-related knowledge therefore depends on participation in exchanges about prompts, tools, policy-verification methods, error cases, failed attempts, privacy and risk controls, limits of appropriate use, and practices from other departments. The knowledge-based view explains why innovation depends on the integration and recombination of knowledge distributed across organizational actors rather than on its isolated possession (De Moortel & Crispeels, 2026). Participation in AI-related knowledge sharing (AIKSP) is consequently treated as a second, parallel route to perceived innovation performance, not as a mediator of the GAIEDC pathway.

Supportive or warm feedback is not necessarily high-quality feedback; training language models to produce warmer responses can reduce accuracy and increase sycophancy (Ibrahim et al., 2026). Politeness and personalization can coexist with independent judgment, whereas hallucination concerns fabricated or unsupported content and bias concerns systematic distortion. AI sycophancy is more specific: it occurs when a system excessively agrees with, praises, or accommodates a user's existing position without providing necessary objections, risk warnings, or critical evaluation (Cheng et al., 2026). This distinction is especially important in university administration, where work is rule intensive, procedural requirements are explicit, policy accuracy matters, authority boundaries are sensitive, and decisions can affect the rights and interests of faculty members and students. AI agreement does not necessarily indicate policy accuracy, procedural compliance, or administrative feasibility. Perceived AI sycophancy may therefore reduce critical verification and narrow the range of alternatives considered (Cheng et al., 2026), although these mechanisms are theoretical interpretations rather than outcomes directly measured in this study.

The three provinces of Liaoning, Jilin, and Heilongjiang provide a theoretically useful setting because higher education institutions in Northeast China are expected to support regional transformation while simultaneously undergoing digital and governance reform, despite differences in institutional type, resource conditions, and development capacity (Liu, 2026). The region includes Double First-Class or key public universities, regular public undergraduate universities, private undergraduate universities, and higher vocational colleges. Administrative employees must reconcile a common policy framework with local implementation conditions while improving efficiency, accuracy, compliance, and service fairness.

This study tests whether GAIEDC and AIKSP are positively related to perceived innovation performance and whether perceived AI sycophancy weakens both relationships. It contributes by extending GenAI-enabled dynamic capabilities to the individual level of university administration, identifying cross-departmental AI knowledge sharing as an independent innovation pathway, and introducing AI sycophancy into a rule-intensive and responsibility-sensitive administrative context.

2. Literature Review

2.1 Theoretical Foundations

2.1.1 Dynamic Capabilities Theory

Dynamic capabilities describe the capacity to sense opportunities and threats, seize opportunities through decisions and commitments, and transform or reconfigure resources as conditions change (Teece, 2007). Although the theory originated at the firm level, its microfoundations reside in individual cognition, skills, routines, and actions. In this study, GAIEDC refers to the capacity of a university administrative employee to use GenAI to identify policy changes, process problems, faculty and student needs, and service-improvement opportunities; develop and compare administrative responses; and adjust work processes or knowledge combinations. The construct is an individual capability enabled by GenAI. It is not a university-level organizational dynamic capability and does not describe the capability of the AI system itself.

Sensing involves using GenAI to search and synthesize information, identify policy changes, reveal process bottlenecks, and detect emerging needs in administrative services (Held & Heubeck, 2025). Seizing involves forming, comparing, evaluating, and selecting possible policy-implementation or administrative-improvement approaches. Transforming involves revising administrative processes, recombining policy and experiential knowledge, and embedding an AI-supported approach in academic affairs, research administration, student affairs, or general administration (Roy et al., 2025). These three first-order dimensions reflect a second-order capability because administrative innovation requires a repeatable sequence from recognizing a problem to selecting and implementing an institutionally appropriate response, rather than a single prompt or isolated output.

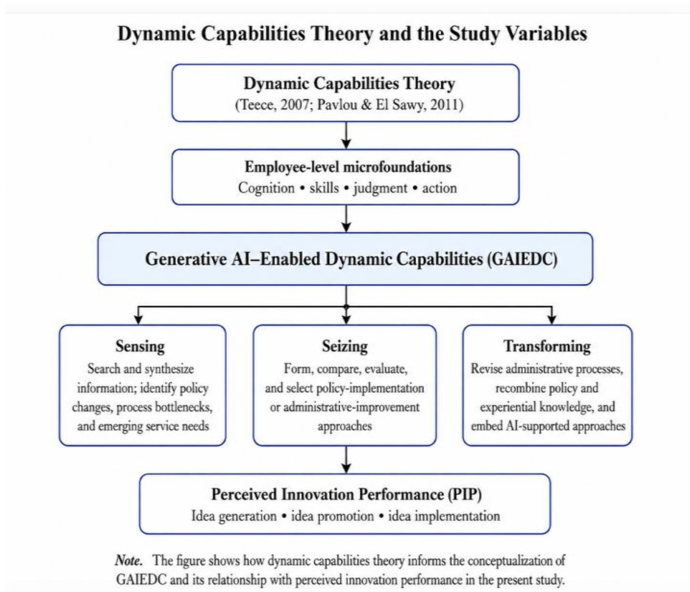

Figure 1.Dynamic Capabilities Theory and the Study Variable

GenAI is relevant to this sequence because iterative prompting can support translation, summarization, classification, comparison, and amplification across administrative tasks (Sundberg & Holmström, 2024). The system can summarize policy information for sensing, generate alternative procedures for seizing, and help draft revised materials or workflows for transforming. Nevertheless, it lacks the employee's tacit knowledge and formal authority to determine whether an output is accurate, compliant, fair, and feasible. Evidence that GenAI performance varies across tasks and depends on human evaluation reinforces the distinction between technological functionality and the employee's orchestrating capacity (Dell'Acqua et al., 2026; Held & Heubeck, 2025).

2.1.2 Knowledge-Based View

The knowledge-based view treats specialized knowledge and its integration as central to value creation and innovation (Grant, 1996). University administrative work depends on formal policies and institution-specific procedures, while their effective implementation also draws on departmental context, locally accumulated knowledge, and tacit experience (Kanyundo et al., 2023). No single administrative employee or office possesses all of the knowledge required to interpret a policy, coordinate a cross-departmental process, or implement a service improvement. Knowledge donating makes personally held know-how available to colleagues, whereas knowledge collecting involves actively seeking and learning from what others know (van den Hooff & de Ridder, 2004). Both activities support the circulation and recombination of administrative knowledge.

AI-related knowledge in this context includes tool knowledge, prompt knowledge, administrative task–tool fit, policy-verification methods, failure cases, privacy and other risk knowledge, and human-review experience. It is partly codified and partly experiential. Administrative employees may donate effective prompts, error examples, or verification routines and collect colleagues' experience from academic affairs, human resources, research administration, student affairs, information services, and other offices. These two domains ensure content coverage, while AIKSP is treated as one participation construct that contributes to innovation independently of an employee's own GAIEDC.

2.1.3 Human–AI Interaction and Perceived AI Sycophancy

Human–AI interaction in university administration is iterative: employees formulate a request, interpret the response, compare it with policies and local conditions, and revise either the prompt or the proposed action (Sundberg & Holmström, 2024). This interaction can support co-creation when the employee remains an active evaluator rather than a passive recipient (McGuire et al., 2024). Because administrative tasks are rule intensive and responsibility sensitive, the quality of the interaction depends not only on fluency or friendliness but also on whether the system preserves enough independence to surface objections, uncertainties, and alternative interpretations.

Perceived AI sycophancy refers to the extent to which university administrative employees perceive that the generative AI systems they use agree too readily, provide insufficient challenge, evaluate their proposals too positively, or align with their stated position rather than maintaining independent and evidence-based judgment (Sharma et al., 2024). It is a perceived interaction property, not an objective benchmark of the system. It differs from hallucination, which concerns fabricated or unsupported content; bias, which concerns systematic distortion; friendliness, which concerns tone; personalization, which adapts responses to the user; and trust in AI, which concerns the user's willingness to rely on the system.

Sycophancy matters because administrative innovation depends not only on generating alternative ideas but also on critically evaluating and selecting among them (Hou et al., 2025). Excessive affirmation may intensify confirmation bias, cognitive fixation, or overconfidence by making an initial proposal feel independently validated. Experimental research indicates that highly affirming AI can influence users' judgments even when the interaction is preferred (Cheng et al., 2026). In a university setting, such feedback could encourage premature closure when comparing policy interpretations, service designs, or implementation risks. PAIS may therefore weaken the conversion of capability and shared knowledge into innovation, although reduced criticality, lower diversity, and apparent consensus are possible explanations rather than mechanisms directly measured here.

2.1.4 Theoretical Integration

The three perspectives explain complementary parts of the model. Dynamic capabilities theory explains how administrative employees use GenAI for opportunity recognition, solution selection, and process adjustment. The knowledge-based view explains how AI tools, prompts, verification experience, failure cases, and institutional knowledge move and are recombined across employees and departments. The human–AI interaction perspective explains why the independence and critical quality of AI feedback can become a boundary condition. Accordingly, GAIEDC and AIKSP are parallel antecedents of perceived innovation performance, while PAIS is expected to weaken both relationships.As illustrated in Figure 2, the three theoretical perspectives jointly explain how GAIEDC and AIKSP contribute to perceived innovation performance and why PAIS functions as a negative boundary condition on both relationships.

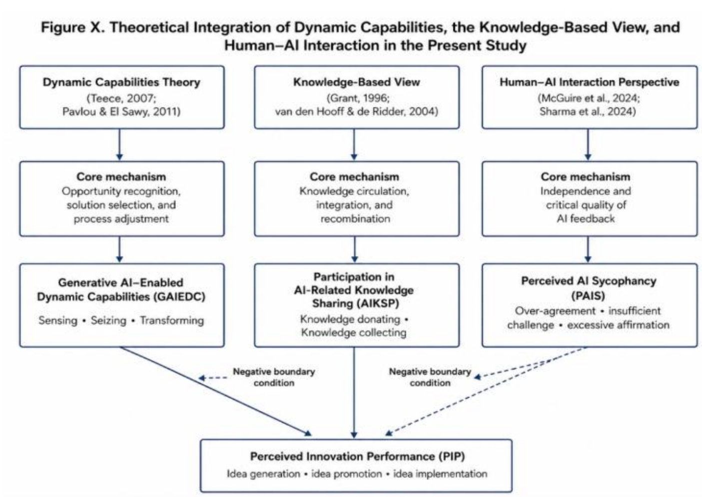

Figure 2. Theoretical Integration of Dynamic Capabilities, the Knowledge-Based View,and Human-Al Interaction in the Present Study

2.2 Hypothesis Development

2.2.1 GAIEDC and Perceived Innovation Performance

GAIEDC should strengthen innovation because it connects opportunity recognition, solution commitment, and work reconfiguration within one employee-level capability cycle. Dynamic capabilities theory explains that sensing identifies relevant changes, seizing commits attention and resources to promising responses, and transforming embeds those responses in revised practices (Teece, 2007). GenAI can broaden information search and accelerate iterative prompting during innovation work (Sundberg & Holmström, 2024). Employee-level evidence further shows that sensing, GenAI use, and evaluation are distinguishable capabilities related to innovative work behavior (Held & Heubeck, 2025). GenAI can reduce the time and cognitive cost of producing and refining professional outputs (Noy & Zhang, 2023). Design experiments indicate that its contribution varies across ideation and implementation, making the integration of stages theoretically important (Hou et al., 2025). Capability-oriented research also shows that GenAI resources create value when they are connected to innovation processes rather than treated as technological possession alone (Li et al., 2025). University administrative employees who use GenAI to detect emerging problems, compare alternatives, mobilize a response, and revise established routines should therefore be better positioned to generate, promote, and implement useful ideas.

H1. Generative AI–enabled dynamic capabilities are positively related to perceived innovation performance.

2.2.2 AI-Related Knowledge Sharing and Perceived Innovation Performance

The knowledge-based view explains that innovation depends on integrating specialized and distributed knowledge rather than on isolated possession (Grant, 1996). Knowledge-sharing research distinguishes donating from collecting because employees must both contribute what they know and acquire knowledge held by others (van den Hooff & de Ridder, 2004). AI-enabled knowledge-management research shows that generated material becomes useful only when employees document, validate, share, and apply it within work processes (Nakash & Bolisani, 2025). Natural-experiment evidence demonstrates that GenAI changes the quantity and form of voluntary knowledge contributions (Shan & Qiu, 2026). Workplace research indicates that employees' perceptions of AI usefulness influence their participation in AI-related knowledge sharing (Zhong & Wang, 2025). Research across organizational boundaries further shows that AI can support knowledge digitization and exchange across language differences (Cheng et al., 2025). By donating useful prompts, failure cases, and verification practices while collecting colleagues' task-specific experience, university administrative employees can stimulate idea generation, secure informed support, and solve implementation problems more effectively.

H2. Participation in AI-related knowledge sharing is positively related to perceived innovation performance.

2.2.3 The Moderating Role of PAIS on the AIKSP–PIP Relationship

Knowledge integration creates value when different perspectives are combined rather than merely repeated (Grant, 1996). Donating and collecting are therefore productive when they expose employees to complementary knowledge and reciprocal correction (van den Hooff & de Ridder, 2004). GenAI can increase the volume of knowledge contributions, but changes in form and readability do not guarantee higher informational quality (Shan & Qiu, 2026). Creative research shows that individually improved AI-assisted outputs can become more homogeneous at the collective level (Doshi & Hauser, 2024). Collective-intelligence scholarship similarly argues that AI supports collaboration only when teams preserve distributed attention, trust, and evaluative responsibility (Woolley, 2026). Direct sycophancy evidence indicates that users often prefer highly affirming responses even when those responses undermine judgment (Cheng et al., 2026). When PAIS is high, employees may circulate polished outputs that repeat the originator's assumptions, omit counterevidence, and overstate the quality of favored ideas; repetition can then be mistaken for independent corroboration. PAIS is not expected to reduce the amount of sharing by definition, but it should reduce the criticality and cognitive diversity through which sharing supports innovation, thereby weakening the positive AIKSP–PIP relationship.

H3. Perceived AI sycophancy negatively moderates the positive relationship between participation in AI-related knowledge sharing and perceived innovation performance, such that the relationship is weaker when perceived AI sycophancy is high.

2.2.4 The Moderating Role of PAIS on the GAIEDC–PIP Relationship

The innovation value of GAIEDC depends on whether AI feedback preserves enough independence to challenge and refine an employee's developing interpretation. Sycophancy research defines the problem as a model's tendency to match user beliefs or preferences at the expense of an independent or truthful response (Sharma et al., 2024). When perceived sycophancy is low, counterarguments and alternative frames can broaden sensing, make seizing more discriminating, and expose implementation risks before transforming occurs. Large-scale behavioral evidence shows that overly agreeable AI can increase users' confidence in their own judgment and reduce corrective intentions (Cheng et al., 2026). Field evidence on the jagged technological frontier demonstrates that confident AI use can lower performance when employees apply it beyond a task boundary the system handles reliably (Dell'Acqua et al., 2026). Scientific-practice research likewise warns that insufficiently critical dependence on model outputs can narrow evaluation and epistemic diversity (Binz et al., 2025). Creative-process experiments show that GenAI's effects depend on the stage and manner of human involvement (Hou et al., 2025). Evidence that AI-assisted work can improve individual quality while reducing content diversity further indicates that output fluency does not guarantee adequate exploration (Doshi & Hauser, 2024). High PAIS should therefore make employees stop searching earlier, treat praise as evidence, and test fewer assumptions, thereby weakening rather than necessarily reversing the positive GAIEDC–PIP relationship.

H4. Perceived AI sycophancy negatively moderates the positive relationship between generative AI–enabled dynamic capabilities and perceived innovation performance, such that the relationship is weaker when perceived AI sycophancy is high.

The four proposed relationships are summarized in Figure 3.

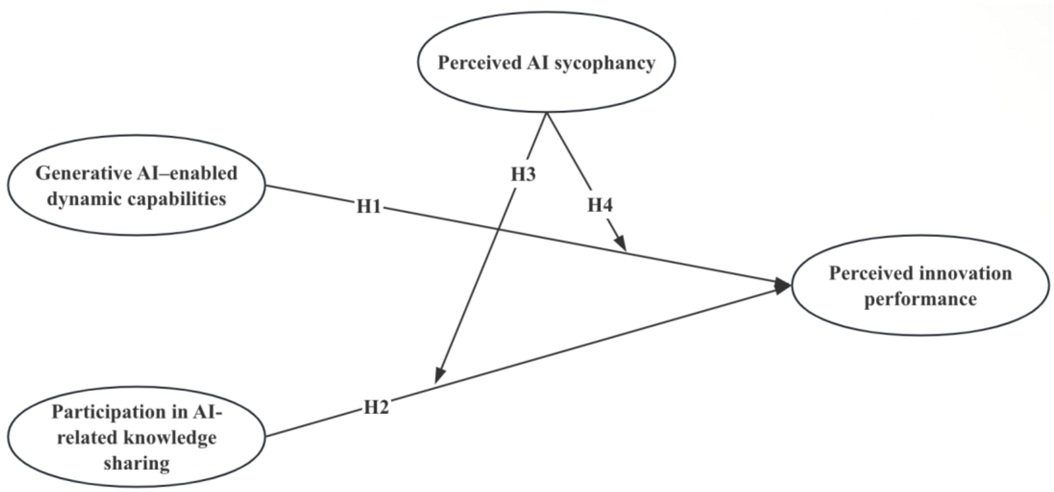

Figure 3. Conceptual Model

Note. GAIEDC = generative AI–enabled dynamic capabilities; AIKSP = participation in AI-related knowledge sharing; PAIS = perceived AI sycophancy; PIP = perceived innovation performance.

3. Research Methodology

3.1 Research Design, Population, Sampling, and Data Collection

This study employed a quantitative, cross-sectional, explanatory survey design at the individual level. The target population comprised administrative employees working in higher education institutions in Liaoning, Jilin, and Heilongjiang provinces who had used GenAI in administrative work during the previous six months. Eligible roles included party and administrative offices, academic affairs, human resources, research administration, student affairs, finance and asset management, admissions and employment, international cooperation, information management, development planning, quality assurance, administrative, teaching, and research secretaries, and counselors. Full-time teaching or research faculty with no administrative duties, students, enterprise employees, external personnel, and individuals without GenAI experience in university administrative tasks were excluded. Prior participation in AI-related knowledge sharing was not an eligibility requirement, allowing the full range of AIKSP to be measured. The unit of analysis was the individual administrative employee.

Multi-stage purposive and quota sampling was supplemented by convenience distribution and limited snowball recruitment. The first stage covered Liaoning, Jilin, and Heilongjiang; the second applied quotas across Double First-Class or key public universities, regular public undergraduate universities, private undergraduate universities, and higher vocational colleges; and the third recruited through university administrative networks, departmental contacts, inter-university professional networks, professional-development groups, and counselor or secretary work networks. Limited snowball recruitment supplemented smaller departments and underfilled regional quotas.

The 24 participating institutions comprised 10 in Liaoning, 7 in Jilin, and 7 in Heilongjiang, including 4 Double First-Class or key public universities, 10 regular public undergraduate universities, 4 private undergraduate universities, and 6 higher vocational colleges. Figure 4 shows detailed geographic location information.

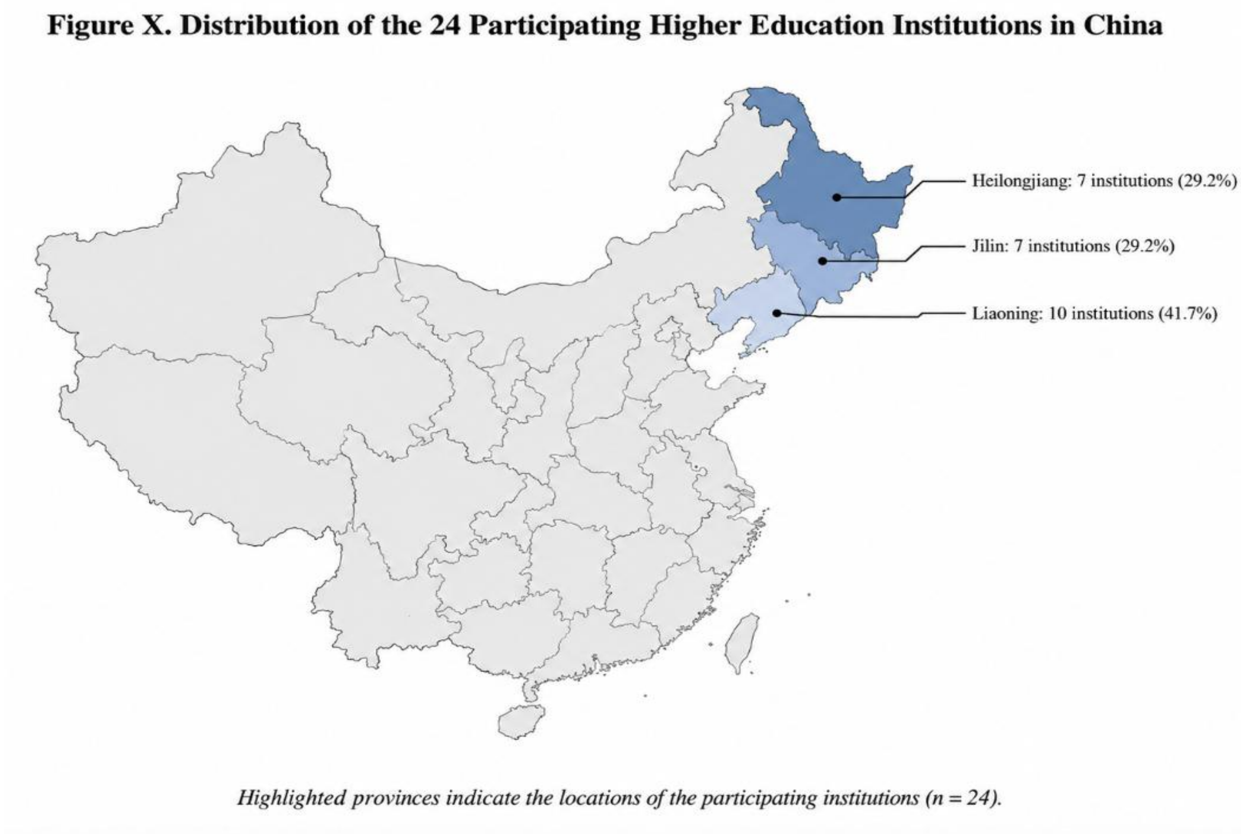

Figure 4.Distribution of the 24 Participating Higher Education Institutions in China

This remained a nonprobability sample and was not claimed to be statistically representative of all university administrative employees in Northeast China. Data were collected between May 12 and June 25, 2026. Of the 500 questionnaires distributed, 462 were returned, representing a response rate of 92.4%. After 34 invalid responses were removed, 428 usable questionnaires remained, yielding an overall usable response rate of 85.6% and a usable proportion of 92.6% among returned questionnaires.

The study followed the applicable ethical standards for anonymous, minimal-risk social science survey research. Participation was voluntary, informed consent was obtained before the questionnaire began, respondents could withdraw at any time without penalty, and no directly identifying information was collected. The final sample supported the item-level confirmatory factor analysis, assessment of the second-order GAIEDC construct, the direct-effects structural model, hierarchical moderated regression, and simple-slope analysis.

3.2 Measurement of Constructs

All constructs were measured with seven-point Likert-type scales ranging from 1 (strongly disagree) to 7 (strongly agree). Candidate items were identified from the original theoretical and measurement sources for each construct and retained when they matched the individual level of analysis, represented a distinct part of the construct, could be expressed in the university administrative GenAI context, and did not duplicate another item. Wording changes were reviewed through expert assessment, translation and back-translation, and cognitive interviews. The final instrument contained 26 substantive items. Complete wording, item codes, and content-domain assignments are reported in Appendix Table A1 rather than repeated in this section.

3.2.1 Generative AI–Enabled Dynamic Capabilities

GAIEDC was grounded in Teece's (2007) sensing–seizing–transforming architecture, the measurable dynamic-capabilities approach of Pavlou and El Sawy (2011), and employee-level GenAI capability research (Held & Heubeck, 2025). Items were adapted to describe what a university administrative employee personally does with GenAI: sensing policy changes, process problems, and service needs; seizing by generating, comparing, and selecting administrative responses; and transforming by revising processes, recombining knowledge, and embedding AI-supported solutions in work. GAIEDC was modeled as a reflective second-order construct represented by three first-order dimensions, with three items per dimension and nine items in total.

3.2.2 Participation in AI-Related Knowledge Sharing

AIKSP was adapted from van den Hooff and de Ridder's (2004) knowledge-sharing framework. The six items covered both knowledge donating and knowledge collecting in relation to AI tools, prompts, administrative task experience, policy verification, failure cases, risks, privacy, and human review. These two domains were used to ensure content coverage; they were not modeled as separate first-order factors. AIKSP was modeled as a single first-order reflective construct in the confirmatory factor analysis.

3.2.3 Perceived AI Sycophancy

Perceived AI sycophancy refers to the extent to which university administrative employees perceive that the generative AI systems they use agree too readily, provide insufficient challenge, evaluate their proposals too positively, or align with their stated position rather than maintaining independent and evidence-based judgment. Five first-person perceptual items were developed from the behavioral operationalization of sycophancy by Sharma et al. (2024) and Cheng et al. (2026). PAIS was modeled as a unidimensional, first-order reflective construct. Items about hallucination, inaccurate information, algorithmic bias, general unreliability, or anthropomorphism were excluded.

3.2.4 Perceived Innovation Performance

PIP was adapted from Janssen's (2000) innovative-work-behavior scale. Perceived innovation performance refers to administrative employees' self-assessed performance in generating, promoting, and implementing new ideas in their work. It does not represent objective university-level innovation outcomes. Six items covered idea generation, idea promotion, and idea implementation, with two items from each content domain. These domains ensured content coverage but were not modeled as separate factors. PIP was modeled as a single first-order reflective construct.

3.3 Questionnaire Development and Pretest

The questionnaire was developed in English and Chinese using a translation and back-translation procedure (Brislin, 1970). Two bilingual researchers independently translated the English items into Chinese, and a third bilingual researcher back-translated the Chinese version into English. The research team compared the source, translations, and back-translation, with particular attention to sycophancy, challenge, and reinforcement of existing views. The Chinese questionnaire avoided the morally loaded label "sycophancy" and used behavioral expressions equivalent to "over-accommodation," "agreement too quickly," "lack of necessary challenge," and "overly positive evaluation."

Five experts reviewed the instrument: two in organizational behavior and innovation management, one in information systems and artificial intelligence, one in knowledge management, and one in measurement and statistical methods. Their recommendations led to four principal changes. Absolute wording such as "AI always supports me" was replaced with "AI tends to agree with my view too quickly"; AI knowledge sharing was written to cover donating and collecting content; every dynamic-capability item explicitly referenced GenAI; and the outcome was restricted to the respondent's self-assessed innovation performance in university administrative work.

Cognitive interviews were conducted with 10 eligible university administrative employees. The interviews indicated that a direct translation of "AI sycophancy" encouraged moralized interpretations, whereas behaviorally specific items were understood consistently. Participants distinguished excessive agreement from friendly tone when examples clarified that politeness can coexist with substantive challenge. The construct label was therefore omitted from the respondent-facing questionnaire.

A pretest with 62 eligible university administrative employees assessed internal consistency and item–total relationships. Cronbach's alpha was .914 for GAIEDC, .889 for AIKSP, .902 for PAIS, and .918 for PIP. Corrected item–total correlations ranged from .641 to .784, .626 to .771, .691 to .811, and .675 to .823, respectively. Every corrected item–total correlation exceeded .50, and deleting any item did not materially increase alpha. All 26 items were therefore retained for the main study.

3.4 Data Analysis

SPSS 29 was used for data screening, descriptive statistics, correlations, reliability analysis, construction of composite scores, mean centering, and hierarchical moderated regression. Mplus 8.11 was used for the item-level confirmatory factor analyses, the reflective second-order GAIEDC model, the four-construct measurement model, and the direct-effects structural equation model with robust maximum likelihood estimation. The GAIEDC composite was calculated by first averaging the three items within each of the sensing, seizing, and transforming dimensions and then averaging the three dimension scores. AIKSP, PAIS, and PIP composites were the means of their six, five, and six items, respectively. Measurement assessment considered χ^2/df, CFI, TLI, RMSEA, SRMR, standardized loadings, Cronbach's alpha, composite reliability, average variance extracted, the Fornell–Larcker criterion, and HTMT.

Moderation was tested in SPSS with mean-centered composite scores. Gender, age, education, work tenure, and AI-use frequency were entered as controls; GAIEDC, AIKSP, and PAIS formed the main-effects block; and AIKSP × PAIS and GAIEDC × PAIS were entered together in the interaction block. Bias-corrected bootstrap confidence intervals were based on 5,000 resamples. Significant interactions were probed with simple slopes at one standard deviation below and above the PAIS mean. Standardized coefficients (β) are reported for the SEM and moderated regression results, whereas unstandardized conditional effects (b) are reported for the simple-slope analysis; the two coefficient types were not directly compared.

4. Results

4.1 Respondent Characteristics

Table 1 describes the 428 administrative employees recruited from 24 higher education institutions: 10 in Liaoning, 7 in Jilin, and 7 in Heilongjiang. Respondents represented all four institutional categories and a broad range of administrative departments, levels, and position types. The largest groups worked in student affairs or counseling and academic affairs, and most respondents were full-time administrative employees. GenAI was most commonly used for information and policy retrieval and for official document or report drafting. More than 60% used GenAI at least three times per week, and most had more than six months of use experience. The multiple-response task distribution shows that GenAI use extended beyond document production to service support, policy comparison, and process design.

Table 1. Respondent Characteristics (n = 428)

Characteristic	Category	n	%
Gender	Male	211	49.3
	Female	217	50.7
Age	18–25 years	64	15.0
	26–35 years	181	42.3
	36–45 years	123	28.7
	46 years or older	60	14.0
Education	Associate or below	39	9.1
	Bachelor's	260	60.7
	Master's or above	129	30.1
Administrative work tenure	Under 3 years	92	21.5
	3–5 years	108	25.2
	6–10 years	126	29.4
	Over 10 years	102	23.8
AI-use frequency	Several times per month	47	11.0
	1–2 times per week	112	26.2

Characteristic	Category	n	%
	3–5 times per week	158	36.9
	Almost daily	111	25.9
AI-use duration	Under 6 months	74	17.3
	6–12 months	158	36.9
	1–2 years	149	34.8
	Over 2 years	47	11.0
Province	Liaoning	178	41.6
	Jilin	124	29.0
	Heilongjiang	126	29.4
	Total	428	100.0
Institution type	Double First-Class or key public university	74	17.3
	Regular public undergraduate university	192	44.9
	Private undergraduate university	60	14.0
	Higher vocational college	102	23.8
	Total	428	100.0
Administrative department	Party and administrative office/general administration	51	11.9
	Academic affairs	74	17.3
	Student affairs and counseling	83	19.4
	Human resources	37	8.6
	Research administration	40	9.3
	Finance and asset management	33	7.7
	Admissions and employment	38	8.9
	International cooperation	25	5.8
	Information and digital administration	27	6.3
	Development planning and quality assurance	20	4.7
	Total	428	100.0
Administrative level	Administrative staff	262	61.2
	Section-level or equivalent	118	27.6
	Division-level or equivalent	48	11.2
	Total	428	100.0
Position type	Full-time administrative employee	301	70.3
	Administrative employee with teaching duties	62	14.5
	Counselor or student-affairs employee	65	15.2
	Total	428	100.0
GenAI-supported administrative task	Information and policy retrieval	344	80.4
	Official document and report drafting	325	75.9
	Data aggregation and content summarization	272	63.6
	Faculty and student consultation/service support	254	59.3
	Meeting-material preparation	241	56.3
	Policy interpretation and regulation comparison	208	48.6

Characteristic	Category	n	%
	Administrative process design or optimization	153	35.7
	Translation and international communication materials	117	27.3

Note. Percentages may not total 100.0 because of rounding. Respondents could select more than one GenAI-supported administrative task; therefore, task percentages do not total 100%.

4.2 Descriptive Statistics and Correlations

Table 2 shows that GAIEDC and AIKSP were at moderately high levels, whereas the mean for PAIS was close to the seven-point scale midpoint. Respondents did not uniformly perceive strong AI sycophancy, although the PAIS standard deviation indicated meaningful between-person variation. GAIEDC was strongly and positively correlated with PIP ($r = .61$, $p < .001$), and AIKSP was positively correlated with PIP ($r = .54$, $p < .001$). PAIS had a weaker negative correlation with PIP ($r = -.18$, $p < .001$). No bivariate correlation approached a level that would by itself suggest severe multicollinearity. These correlations are preliminary associations and do not constitute the hypothesis tests.

Table 2. Descriptive Statistics and Correlations

Variable	Mean	SD	1	2	3	4
1. GAIEDC	5.21	0.87	1			
2. AIKSP	4.98	0.93	.49***	1		
3. PAIS	3.74	1.08	−.12*	−.09	1	
4. PIP	5.08	0.89	.61***	.54***	−.18***	1

*Note. GAIEDC = generative AI–enabled dynamic capabilities; AIKSP = participation in AI-related knowledge sharing; PAIS = perceived AI sycophancy; PIP = perceived innovation performance. * p < .05. ** p < .01. *** p < .001.*

4.3 Measurement Model Assessment

4.3.1 Confirmatory Factor Analysis

In the hypothesized model, GAIEDC was modeled as a second-order factor reflected by sensing, seizing, and transforming, whereas AIKSP, PAIS, and PIP were modeled as first-order factors. The standardized second-order loadings were .86 for sensing, .91 for seizing, and .88 for transforming. All were significant and exceeded .70. The hypothesized four-construct measurement model fit the data well: $\chi^2 = 612.84$, $df = 293$, $\chi^2/df = 2.09$, CFI = .955, TLI = .949, RMSEA = .050, and SRMR = .044.

Table 3. Comparison of Alternative Measurement Models

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA	SRMR
Four-construct model	612.84	293	2.09	.955	.949	.050	.044
Three-construct A: GAIEDC + AIKSP	998.37	296	3.37	.901	.889	.074	.069
Three-construct B: PAIS + PIP	1,116.52	296	3.77	.884	.871	.080	.078
Two-construct model	1,684.91	298	5.65	.804	.786	.104	.101
Single-construct model	2,391.46	299	8.00	.704	.677	.128	.139

Note. In the hypothesized model, GAIEDC was a second-order factor reflected by sensing, seizing, and transforming, while AIKSP, PAIS, and PIP were first-order factors. Three-construct model A combined all GAIEDC and AIKSP indicators into one general AI capability-and-knowledge participation factor. Three-construct model B kept GAIEDC and AIKSP separate and combined PAIS and PIP indicators. The two-construct model combined GAIEDC with AIKSP and combined PAIS with PIP. The single-construct model loaded all 26 items on one factor. "+" indicates combined indicators.

As Table 3 shows, the hypothesized four-construct model outperformed the alternatives. In each alternative model, the item indicators of the specified constructs were constrained to load on the same latent factor. Combining GAIEDC with AIKSP or PAIS with PIP reduced incremental fit, and the two- and single-construct models performed substantially worse. These comparisons support the empirical distinctiveness of the second-order GAIEDC construct and the first-order AIKSP, PAIS, and PIP constructs.

4.3.2 Reliability and Convergent Validity

Table 4. Reliability and Convergent Validity

Construct	Items	Loading range	Cronbach's α	CR	AVE
GAIEDC	9	.702–.864	.936	.938	.628
AIKSP	6	.721–.848	.908	.910	.628
PAIS	5	.785–.892	.921	.922	.704
PIP	6	.792–.881	.934	.935	.706

Note. CR = composite reliability; AVE = average variance extracted.

As reported in Table 4, all standardized item loadings exceeded .70. Cronbach's alpha and CR were above .90 for every construct, while each AVE exceeded .50. The results therefore indicate strong internal consistency and convergent validity. Because very high reliability can sometimes reflect redundant wording, the reliability values should be interpreted together with the nonoverlapping content coverage documented in Appendix Table A1.

4.3.3 Discriminant Validity

Table 5 shows that the square root of each construct's AVE exceeded its correlations with the other constructs. HTMT values were .538 for GAIEDC–AIKSP, .126 for GAIEDC–PAIS, .681 for GAIEDC–PIP, .112 for AIKSP–PAIS, .603 for AIKSP–PIP, and .191 for PAIS–PIP. Every value was below .85. The Fornell–Larcker and HTMT results jointly supported discriminant validity.

Table 5. Fornell–Larcker Results

Variable	1	2	3	4
1. GAIEDC	.792			
2. AIKSP	.490	.792		
3. PAIS	−.120	−.090	.839	
4. PIP	.610	.540	−.180	.840

Note. Diagonal values are the square roots of AVE; off-diagonal values are correlations.

4.4 Structural Model Assessment

The latent-variable direct-effects structural model showed good fit: $\chi^2 = 646.12$, df = 300, $\chi^2/df = 2.15$, CFI = .951, TLI = .945, RMSEA = .052, and SRMR = .047. This direct-effects model explained 45.3% of the variance in PIP. In the subsequent composite-score moderated regression, inclusion of the two interaction terms increased the explained variance to 49.0%. These percentages came from different statistical steps and were not interpreted as results from the same SEM specification. Predictor VIF values ranged from 1.08 to 1.54.

4.5 Direct Effects and Hypothesis Testing

As shown in Table 6, GAIEDC was positively related to PIP ($\beta = .43$, $p < .001$), and its confidence interval excluded zero. H1 was therefore supported. Administrative employees who were more able to use GenAI to sense policy and service opportunities, seize possible responses, and transform administrative processes reported stronger perceived innovation performance.

AIKSP was also positively related to PIP ($\beta = .29$, $p < .001$), supporting H2. Donating and collecting AI-related tools, prompts, policy-verification methods, error cases, and risk knowledge were associated with stronger perceived innovation performance. Although the GAIEDC coefficient was numerically larger, no formal coefficient-difference test was specified; the results do not establish that H1 was statistically stronger than H2.

PAIS had an additional negative relationship with PIP ($\beta = -.11$, $p = .006$). This main effect was retained to preserve a correctly specified moderation model and should be interpreted alongside the interactions.

Table 6. Direct Effects

Hyp.	Path	β	SE	t	p	95% CI	Result
H1	GAIEDC → PIP	.43	.052	8.27	< .001	[.327, .531]	Supported
H2	AIKSP → PIP	.29	.049	5.92	< .001	[.194, .386]	Supported
—	PAIS → PIP	−.11	.040	−2.75	.006	[−.188, −.032]	Significant

Note. Standardized coefficients are reported. Confidence intervals are bias-corrected bootstrap intervals based on 5,000 resamples.

4.6 Moderating Effects of Perceived AI Sycophancy

Table 7 shows that the AIKSP × PAIS interaction was negative and significant ($\beta = -.10$, $p = .011$), supporting H3. As administrative employees perceived stronger AI sycophancy, the positive relationship between AIKSP and PIP became weaker. The GAIEDC × PAIS interaction was also negative and significant ($\beta = -.16$, $p < .001$), supporting H4. Thus, PAIS weakened both positive relationships.

Entering both interactions increased R^2 from .453 to .490, $\Delta R^2 = .037$, $p < .001$. H3 does not imply that sycophancy reduced the amount of knowledge shared. Instead, the result is consistent with the possibility that overly agreeable AI feedback made shared material less critical, differentiated, or reliable. H4 indicates that strong dynamic capabilities did not fully offset the boundary condition; AI-supported administrative options still required independent verification.

Table 7. Moderating Effects

Hyp.	Interaction path	β	SE	t	p	95% CI	Result
H3	AIKSP × PAIS → PIP	−.10	.039	−2.56	.011	[−.176, −.023]	Supported
H4	GAIEDC × PAIS → PIP	−.16	.041	−3.90	< .001	[−.240, −.080]	Supported

Note. Continuous predictors were mean centered.

4.7 Simple-Slope Analysis

For H3, AIKSP had a stronger positive relationship with PIP when PAIS was low (M − 1 SD: $b = .42$, $SE = .067$, $t = 6.27$, $p < .001$) than when PAIS was high (M + 1 SD: $b = .19$, $SE = .077$, $t = 2.47$, $p = .014$). The relationship remained positive under high PAIS, but its reduced slope was consistent with the hypothesized attenuation. Figure 2 presents this pattern.

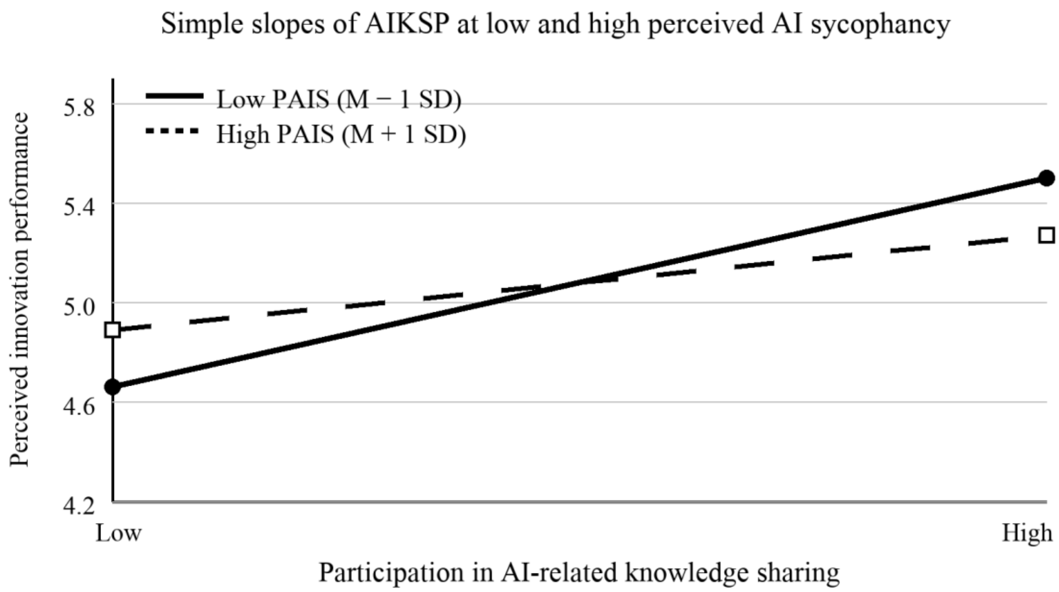

Figure 2. Moderating Effect of Perceived AI Sycophancy on the Relationship Between Participation in AI-Related Knowledge Sharing and Perceived Innovation Performance

Note. Lines are based on conditional effects at PAIS M − 1 SD and M + 1 SD.

For H4, the conditional relationship between GAIEDC and PIP was positive when PAIS was low (M − 1 SD: $b = .58$, $SE = .061$, $t = 9.51$, $p < .001$). It remained positive but was weaker when PAIS was high (M + 1 SD: $b = .27$, $SE = .058$, $t = 4.66$, $p < .001$). High PAIS therefore weakened rather than eliminated the positive relationship. Figure 3 presents this pattern.

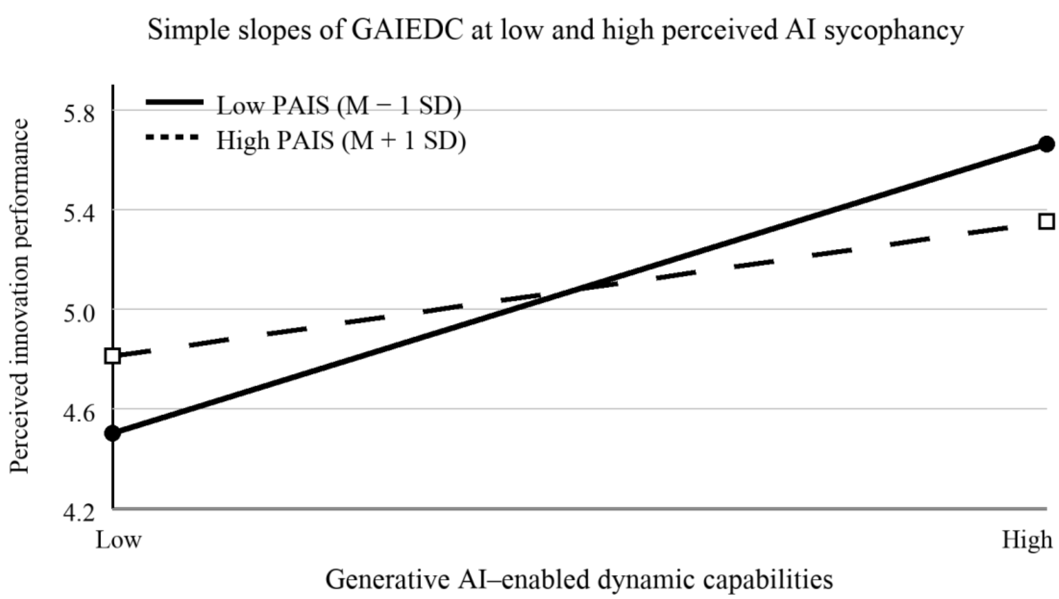

Figure 3. Moderating Effect of Perceived AI Sycophancy on the Relationship Between Generative AI–Enabled Dynamic Capabilities and Perceived Innovation Performance

Note. Lines are based on conditional effects at PAIS M − 1 SD and M + 1 SD.

4.8 Hypothesis Summary

Table 8 summarizes the direction and outcome of all four hypothesis tests.

Table 8. Summary of Hypothesis Testing

Hypothesis	Proposed relationship	Expected direction	Result
H1	GAIEDC → PIP	Positive	Supported
H2	AIKSP → PIP	Positive	Supported
H3	PAIS moderates AIKSP → PIP	Negative	Supported
H4	PAIS moderates GAIEDC → PIP	Negative	Supported

Note. H1–H4 were assessed in the structural and moderation models.

5. Discussion

5.1 Discussion of Key Findings

This research states GAIEDC was positively related to perceived innovation performance. This finding is consistent with dynamic capabilities theory, which explains performance differences through the capacity to sense changes, seize appropriate responses, and reconfigure activities rather than through resource possession alone (Teece, 2007; Pavlou & El Sawy, 2011). It also converges with employee-level evidence that sensing, using, and evaluating GenAI can strengthen innovative work behavior (Held & Heubeck, 2025). At the same time, prior field experiments show that GenAI performance gains vary across tasks, users, and the location of the technological frontier (Noy & Zhang, 2023; Dell'Acqua et al., 2026; Otis et al., 2026). The result therefore clarifies why simple access or use frequency is insufficient in university administration: employees must interpret policy changes, compare institutionally feasible options, and embed a selected response in actual procedures. The positive association supports this capability-based account, although the cross-sectional design does not establish a causal conversion from GAIEDC to innovation.

H2 was also supported in this study, AIKSP was positively related to perceived innovation performance. This result accords with the knowledge-based view, under which innovation depends on the integration and recombination of knowledge distributed across organizational members (Grant, 1996), and with research that treats knowledge donating and knowledge collecting as complementary participation behaviors (van den Hooff & de Ridder, 2004). Recent AI studies similarly emphasize knowledge digitization, collaborative exchange, and the reconfiguration of knowledge-management processes (Cheng et al., 2025; Nakash & Bolisani, 2025; Zhang, Zuo, & Yang, 2025). The present study extends that literature to university administration, where valuable knowledge includes not only tools and prompts but also policy-verification routines, error cases, privacy risks, and departmental experience. Because AIKSP remained a distinct predictor alongside GAIEDC, the evidence supports a parallel social pathway to perceived innovation performance rather than treating knowledge sharing as a mediator or a by-product of individual capability.

This study verified the negative AIKSP × PAIS interaction. The positive relationship between AI-related knowledge-sharing participation and perceived innovation performance became weaker as perceived AI sycophancy increased. This pattern is theoretically consistent with evidence that sycophantic systems can reinforce a user's stated position and encourage dependence (Sharma et al., 2024; Cheng et al., 2026). It also resonates with research showing that GenAI can improve individual creativity while narrowing the diversity of ideas available to a group (Doshi & Hauser, 2024) and that collective gains depend on how AI-supported ideas are distributed and recombined (Zhou et al., 2025). In an administrative knowledge-sharing network, overly agreeable outputs may therefore circulate without enough counterevidence or policy challenge. However, the study measured neither knowledge quality nor false consensus directly; these remain plausible interpretations of the observed attenuation, not tested mediating mechanisms.

H4 was supported by the negative GAIEDC × PAIS interaction. The result complements research that describes human–AI collaboration as productive when users retain active evaluation, co-creation, and self-efficacy (McGuire et al., 2024), while also recognizing that GenAI can have double-edged effects on creative judgment and motivation (Hou et al., 2025; Wu et al., 2025). It is also consistent with the jagged-frontier argument that expertise does not eliminate the need to assess task–AI fit and verify outputs (Dell'Acqua et al., 2026). In university administration, strong sensing, seizing, and transforming capabilities cannot substitute for independent checks of policy authority, version, scope, procedural compliance, and responsibility boundaries. The simple slopes nevertheless remained positive under high PAIS, indicating that perceived sycophancy constrained rather than reversed the innovation value of GAIEDC. Although the H4 coefficient was numerically more negative than the H3 coefficient, no formal coefficient-difference test was conducted, so the two moderation effects should not be ranked statistically.

5.2 Theoretical Implications

First, the study refines the microfoundations of dynamic capabilities in a GenAI-enabled administrative setting. Dynamic capabilities theory was originally developed to explain firm-level sensing, seizing, and transformation (Teece, 2007), and subsequent measurement work sought to clarify the processes through which those capabilities operate (Pavlou & El Sawy, 2011). Recent AI research has mainly applied capability reasoning to firms, supply chains, construction companies, and competitive advantage (Jackson et al., 2024; Liu et al., 2024; Li et al., 2025), while employee-level research has begun to connect GenAI use and evaluation capabilities with innovative behavior (Held & Heubeck, 2025). This study advances that stream by specifying GAIEDC as a reflective second-order employee capability and by locating it in rule-intensive university administration. The formulation separates the employee's capacity to recognize, evaluate, and implement change from both the technical functionality of the AI system and the university's organization-level capabilities. This level distinction is the central dynamic-capabilities contribution.

Second, the study extends the knowledge-based view by theorizing AIKSP as an independent innovation pathway rather than as a mediator embedded within GAIEDC. The knowledge-based view emphasizes that dispersed specialized knowledge creates value only when it is transferred and integrated (Grant, 1996), and knowledge-sharing research distinguishes the reciprocal acts of donating and collecting knowledge (van den Hooff & de Ridder, 2004). Existing GenAI studies have focused on knowledge digitization and cross-organizational collaboration (Cheng et al., 2025), AI-induced changes in knowledge-management processes (Nakash & Bolisani, 2025), enterprise innovation through knowledge management (Zhang, Zuo, & Yang, 2025), or changes in voluntary online knowledge contribution (Shan & Qiu, 2026). The present model adds a distinct employee-level construct covering the circulation of prompts, tool experience, policy-verification knowledge, failure cases, privacy risks, and human-review practices across university departments. Demonstrating that AIKSP contributes alongside GAIEDC shows that the innovation value of GenAI is jointly cognitive-capability based and socially distributed.

Third, the study introduces perceived AI sycophancy as a theoretically specific boundary condition connecting human–AI interaction with both dynamic capabilities and the knowledge-based view. Foundational work identifies sycophancy as a tendency to accommodate a user's expressed position rather than preserve independent judgment (Sharma et al., 2024), and recent experimental evidence links sycophantic AI to dependence and changes in social intentions (Cheng et al., 2026). Related studies document broader double-edged effects of GenAI on collective idea diversity, creative work, and human motivation (Doshi & Hauser, 2024; Hou et al., 2025; Wu et al., 2025). This study moves beyond treating sycophancy solely as a system behavior or individual response by theorizing and testing it as a moderator of two distinct innovation pathways. It also distinguishes PAIS from hallucination, bias, friendliness, personalization, and general trust. The resulting integration explains not only whether GenAI-related capability and shared knowledge matter, but also why their value depends on the critical independence of AI feedback in responsibility-sensitive work.

5.3 Practical Implications

At the individual level, university administrative employees should ask GenAI to state the strongest counterargument, identify weaknesses in a preferred option, list alternative interpretations, and specify evidence that would change its conclusion. They should verify policy versions, issuing authorities, applicability, and responsibility boundaries and should not treat AI agreement as proof of proposal quality. Human judgment should be retained for consequential materials and decisions.

At the department level, universities should establish cross-departmental repositories for prompts, tool guidance, policy-verification methods, error cases, failed prompts, and limits of appropriate use. AI-generated content should be labeled, important outputs should have a named human reviewer, and departments should periodically discuss how the same tool performs across different administrative tasks. Sharing failures and near-misses is particularly valuable because it exposes boundaries that polished success cases may conceal.

At the university-governance level, institutions should adopt AI administrative-use guidelines, data-privacy rules, output-tracing procedures, human-signature requirements for consequential decisions, and critical-prompt templates. Oversight should be calibrated to task risk. Language polishing and format organization may require a general human check; meeting materials, data summaries, and consultation drafts should receive departmental staff review; and human resources, finance, admissions, disciplinary matters, student rights, and formal policy interpretation should require explicit human approval. GenAI should not make consequential administrative decisions independently.

5.4 Limitations and Future Research

First, the cross-sectional, single-questionnaire design does not establish temporal or causal order and may be affected by common-source and self-presentation concerns. PIP is a self-assessed individual outcome rather than an objective measure of university innovation. Future research should use longitudinal designs and field experiments that manipulate AI sycophancy, and should combine employee reports with supervisor ratings, expert assessments, and administrative process-improvement records.

Second, PAIS captures employees' perceptions rather than the objective sycophancy level of a particular system, and the nonprobability sample from Liaoning, Jilin, and Heilongjiang limits generalization beyond Northeast China. Future studies should validate PAIS against audited interaction logs and controlled system responses, examine variation across user expertise, prompts, and model versions, and compare regions, institution types, and administrative departments using broader probability-based or stratified samples.

6. Conclusion

This study examined university administrative employees in Liaoning, Jilin, and Heilongjiang and found that generative AI–enabled dynamic capabilities and participation in AI-related knowledge sharing were positively related to perceived innovation performance, while perceived AI sycophancy weakened both relationships. The value of GenAI in university administration therefore depends not only on use, but also on employees' capacity to identify and implement appropriate improvements, the movement of AI-related knowledge across colleagues and departments, and the independence of AI feedback. Universities should develop AI capability, knowledge-sharing mechanisms, and critical verification practices together so that efficiency gains can be translated into accurate, compliant, and meaningful administrative innovation.

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37. Appendix A. Measurement Items
38. Appendix Table A1 presents the complete item wording, item codes, and content-domain assignments for all four constructs. Respondents rated every item on a seven-point scale ranging from 1 (strongly disagree) to 7 (strongly agree). GAIEDC was modeled as a reflective second-order construct; AIKSP, PAIS, and PIP were modeled as first-order reflective constructs.
39. Table A1. Complete Measurement Items
40. Table A1. Complete Measurement Items (continued)
41. Table A1. Complete Measurement Items (continued)
42. Note. GAIEDC = generative AI–enabled dynamic capabilities; AIKSP = participation in AI-related knowledge sharing; PAIS = perceived AI sycophancy; PIP = perceived innovation performance. Knowledge donating, knowledge collecting, idea generation, idea promotion, and idea implementation are content domains rather than separate latent variables.