GenAI–Sustainability Nexus: Mediating Roles of Knowledge Management and Social Responsibility in HEIs

Raushan Amantayeva, Nalima Sartanova and Liliya Baizhanova
Akhmet Baitursynuly Kostanay Regional University, Kazakhstan
Raunur88@mail.ru (corresponding author)
nalimas@mail.ru
baizhanova2026@bk.ru

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Abstract: Generative Artificial Intelligence (GenAI) is rapidly reshaping knowledge processes in higher education, yet its contribution to Sustainable Performance (SP) remains unclear. This study investigates how GenAI use affects the sustainable performance of higher education institutions (HEIs), where SP is conceptualised as a multidimensional outcome encompassing financial, environmental and social performance. Drawing on the Resource-Based View, the Knowledge-Based View and Stakeholder Theory, the study proposes that GenAI creates value indirectly through two organisational capabilities: Knowledge Management Capability (KMC) and Institutional Social Responsibility (ISR). Survey data were collected from 387 instructors in Kazakhstani colleges who actively use GenAI tools in their work, and analysed using partial least squares structural equation modelling with higher-order constructs. The results show that GenAI does not directly enhance SP, but is positively associated with KMC, which in turn has a strong positive effect on SP. ISR is also positively related to SP, yet GenAI has no significant direct effect on ISR. Mediation analysis reveals that KMC mediates the GenAI–SP relationship, and that GenAI contributes to SP through a significant serial pathway GenAI → KMC → ISR → SP, while ISR alone does not mediate the GenAI–SP link. The findings extend existing theory by demonstrating that GenAI acquires strategic value only when embedded in robust knowledge-management and responsibility structures. Practically, the study highlights the need for HEIs in transition economies such as Kazakhstan to move from tool-centred GenAI adoption towards capability-driven strategies that strengthen KMC and formalise ISR in order to achieve financial, environmental and social gains.

Keywords: Generative artificial intelligence, Sustainable performance, Knowledge management capability, Institutional social responsibility, Higher education, Kazakhstan, PLS-SEM

1. Introduction

The rapid spread of Generative Artificial Intelligence (GenAI) is transforming content production, knowledge processes and digital interactions in education (Nikolopoulou, 2025), while also being increasingly recognised as a driver of sustainable and socially responsible development (Humble and Mozelius, 2024).

Although GenAI is widely expected to support sustainable development across the financial, environmental and social dimensions of sustainable performance (SP) (Shen and Badulescu, 2025), its actual contribution to SP in universities remains theoretically assumed rather than empirically demonstrated (Torrent-Sellens, Enache-Zegheru and Ficapal-Cusí, 2025; Al-Emran, Abu-Hijleh and Alsewari, 2024). This uncertainty is reinforced by growing expectations for universities to embed sustainability into their core strategies (Iqbal and Piwowar-Sulej, 2022) and by the increasing urgency of sustainability transitions within higher education (HE) (Azizi, 2023).

HEIs represent a particularly important context for examining GenAI, as they actively integrate GenAI into curricula, pedagogical strategies, and institutional practices, recognising its transformative potential to enhance educational outcomes, foster critical thinking, and prepare students for future careers. Integrating GenAI into HE is considered crucial for developing future generations of AI-literate professionals and enabling institutions to respond effectively to technological and societal transformations (Jin et al., 2025).

This institutional role is evident in Kazakhstan. For example, Satbayev University (2025) rose by 110 positions in the QS Sustainability Rankings 2025, ranking 771st globally with strong performance in governance (81.1/100) and environmental education (74.4/100), reflecting the growing institutionalization of ESG principles within Kazakhstani HEIs. At the same time, Nazarbayev University (2023) has committed to integrating GenAI into its teaching and governance processes through capacity development and institutional guidelines, illustrating how universities build organisational capabilities for the effective and sustainable use of GenAI.

Despite these developments, the mechanisms through which GenAI contributes to SP in HEIs remain insufficiently understood. Existing research remains fragmented, as most studies focus on GenAI adoption or

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user attitudes (Al-Emran et al., 2025; Al-Qaysi et al., 2025) rather than the organisational mechanisms that connect GenAI to SP. Even in advanced HE systems, university social responsibility remains weakly institutionalised (Detyna and Detyna, 2025), and no empirical research has examined these mechanisms in emerging contexts such as Kazakhstan.

To clarify how GenAI may contribute to sustainability, this study draws on the Resource-Based View (RBV) (Barney, 1991), the Knowledge-Based View (KBV) (Grant, 1996), and Stakeholder Theory (Freeman, 1984). Together, they suggest that GenAI generates value not directly, but through organisational capabilities—particularly KMC and ISR.

Kazakhstan provides a compelling context for examining these mechanisms. While national strategies emphasise digitalisation and sustainability, recent evidence shows uneven digital maturity, underdeveloped knowledge-management (KM) practices, declining SDG-related research engagement, and fragmented responsibility structures across HEIs (Gafu et al., 2025; Jamanbalayeva et al., 2025). These constraints underscore the need to examine how internal capabilities, particularly KMC and ISR, enable HEIs to translate GenAI adoption into SP.

Accordingly, this study examines how GenAI influences the SP of HEIs through the mediating roles of KMC and ISR. By integrating these dimensions into a single explanatory model and testing it in the underexplored context of Kazakhstan, the study advances understanding of how AI-enabled capabilities are translated into sustainability outcomes and provides evidence relevant for both theory development and institutional practice.

2. Literature Review and Hypotheses Development

Building on the study's context and research problem, this section synthesizes prior work on GenAI, KMC, ISR, and SP, drawing on RBV, KBV, and Stakeholder Theory to establish the theoretical grounding of the model. It further considers the implications of this literature for HEIs in Kazakhstan and uses this synthesis to formulate the study's hypotheses.

2.1 Generative Artificial Intelligence and Sustainable Performance

In Kazakhstani HEIs, GenAI may support financial sustainability by improving efficiency amid rising digitalisation costs (Gafu et al., 2025). Evidence from HE suggests that AI-supported digitalisation can streamline administrative processes and improve energy efficiency, generating long-term cost savings (Humble and Mozelius, 2024; Nikolopoulou, 2025). However, GenAI also requires significant infrastructure, which remains uneven across Kazakhstani HEIs (Jamanbalayeva et al., 2025). Increased electricity use and integration costs may offset short-term savings, linking the financial implications of GenAI adoption to its environmental impact (Humble and Mozelius, 2024).

This environmental dimension is especially relevant in Kazakhstan, where green transition policies emphasise technological innovation and resource efficiency (Rakhymzhan et al., 2024). In this context, GenAI may support greener organisational processes through energy optimisation, waste reduction, and resource-efficient innovation (Khan, Mehmood and Kwan, 2024). However, the relationship between GenAI adoption and environmental performance in HEIs remains underexplored.

In HE, GenAI may also support social sustainability by improving accessibility and inclusion (Nikolopoulou, 2025; Al-Emran, Abu-Hijleh and Alsewari, 2024). However, these benefits depend on ethical governance, as AI systems may reproduce biases in training data and exacerbate social disparities, potentially affecting students' well-being and sense of belonging (Francis, Jones, and Smith, 2025).

In Kazakhstan, digital development increasingly highlights the need to balance technological progress with social inclusion (Jamanbalayeva et al., 2025). Yet the practical contribution of GenAI to social sustainability within HEIs remains insufficiently examined at the institutional level, making its broader societal impact difficult to assess.

From an RBV perspective, GenAI can be regarded as a strategic resource that may support multidimensional SP in universities (Barney, 1991; Khan, Mehmood and Kwan, 2024; Shen and Badulescu, 2025). Accordingly, we propose:

H1: GenAI use is positively associated with SP.

2.2 Generative Artificial Intelligence, Knowledge Management Capability, and Sustainable Performance

GenAI demonstrates substantial potential to enhance organisations' KMC—a multidimensional capability reflecting how organisations acquire, share, and apply knowledge to strengthen strategic performance (Gold, Malhotra and Segars, 2001), consistent with the broader conceptualisation of KM proposed by Alavi and Leidner

(2001). From a KBV perspective, knowledge is a strategic resource, and GenAI can support the full knowledge cycle by helping organisations discover, synthesise, share, and apply knowledge across units (Grant, 1996; Jarrahi et al., 2023; Kudryavtsev, Khan and Kauttonen, 2024).

These interrelated processes position KMC as the mechanism through which GenAI-enabled knowledge flows translate into multidimensional SP. Through knowledge acquisition, organisations enhance innovation, decision-making, and environmental practices while strengthening social impact by integrating external expertise (Choi, Chang and Youn et al., 2021; Sahoo et al., 2022). Knowledge sharing further supports eco-innovation, environmental outcomes, and social performance by fostering collaboration and sustainability-oriented initiatives (Ahmad et al., 2023; López-Torres et al., 2026). Finally, knowledge application converts accumulated expertise into process innovations, competitive advantages, and sustainable practices that reinforce financial, environmental, and social outcomes (Kavalić et al., 2021; Martínez-Falcó et al., 2024).

However, recent HE studies typically position KM factors as antecedents of GenAI use, with GenAI use serving as an intervening mechanism linking KM factors to educational or social sustainability (Al-Qaysi et al., 2025; Al-Emran et al., 2025). In contrast, evidence from other sectors shows that KM processes themselves can mediate the link between digital capabilities and SP (Al-Husain et al., 2025).

Extending this perspective, the Kazakhstani HE sector represents a relevant yet underexplored context, where HEIs are actively pursuing digital transformation and sustainability goals while operating within systems of uneven digital maturity and evolving knowledge-management practices (Mendaliyeva et al., 2026).

Accordingly, the following hypotheses are proposed:

H2. GenAI use is positively associated with KMC.

H3. KMC is positively associated with SP.

H4. KMC positively mediates the relationship between GenAI use and SP.

2.3 Generative Artificial Intelligence, Institutional Social Responsibility, and Sustainable Performance

The relationship between GenAI and ISR has recently attracted scholarly attention as organisations seek to align technological innovation with ethical and socially responsible practices (Lim et al., 2025; Della Giovampaola et al., 2025). ISR refers to an institution's commitment to manage its activities transparently and responsibly while addressing stakeholder expectations and contributing to sustainable development (Lozano, 2018).

Grounded in Stakeholder Theory (Freeman, 1984), GenAI can support ISR by strengthening transparency, accountability, and stakeholder engagement within organisational processes. For instance, responsible institutional conduct is reinforced through stronger ethical governance and transparent data practices enabled by GenAI (Lim et al., 2025). Responsible research and innovation are further supported through the development of policies, standards, and infrastructures that guide AI use within HEIs (Smith et al., 2026). In addition, GenAI expands community outreach and social impact through AI-for-Social-Good initiatives and cross-sector partnerships (Della Giovampaola et al., 2025). These practices strengthen stakeholder trust and institutional legitimacy and contribute to broader sustainability outcomes (Latif et al., 2024; Janssen, 2025; Shen and Badulescu, 2025).

ISR can serve as the mechanism through which GenAI-driven innovation is translated into more ethical, transparent, and stakeholder-oriented institutional practices (Detyna and Detyna, 2025; Ouragini and Ben Hassine Louzir, 2024). However, despite its growing relevance in HE, ISR implementation still faces methodological and institutional challenges, particularly in assessing its impact and integrating AI-driven initiatives into responsibility frameworks (Detyna and Detyna, 2025).

In line with global discussions, the Kazakhstani HE sector provides an emerging yet underexplored context for examining the role of ISR in linking GenAI adoption with SP. In Kazakhstan, empirical research on ISR remains limited. Recent studies have primarily focused on individual-level perceptions of ISR and volunteering among university students rather than institutional mechanisms (Utemissova, Abdigapbarova, and Rezuanova, 2025). Moreover, although Kazakhstan's higher-education system has made progress toward internationalization, the existing legal and policy frameworks still lack clear mechanisms for integrating social responsibility principles into institutional governance and performance evaluation (Berdibaev et al., 2024). These limitations constrain the systemic implementation of ISR and its potential to support SP within Kazakhstani HEIs.

Based on this reasoning, we hypothesize:

H5. GenAI use is positively associated with ISR.

H6. ISR is positively associated with SP.

H7. ISR positively mediates the relationship between GenAI use and SP.

2.4 Linking Knowledge Management Capability and Institutional Social Responsibility

KMC has been increasingly recognised as a strategic enabler of social responsibility, since effective knowledge exploration and exploitation foster an organisation's social, environmental, and economic commitments (González-Ramos, Guadamillas and Donate, 2023). Drawing on the KBV (Grant, 1996), knowledge acts as a strategic resource that enables universities to transform intellectual capital into socially valuable practices. Likewise, following the Stakeholder Theory (Freeman, 1984), effective acquisition, sharing, and application of knowledge allow institutions to align their activities with the expectations of both internal and external stakeholders, thereby fostering ISR.

Rather than operating as isolated processes, KMC dimensions collectively shape how responsibility is embedded within institutional practices. The generation of new insights and the integration of external expertise contribute to ethical transparency and responsible research development (Beltrán-Lizárraga et al., 2024; Sobaih et al., 2025). The diffusion of knowledge across organisational units fosters openness, interdisciplinary collaboration, and the dissemination of socially relevant expertise that strengthens community engagement (Liu et al., 2024; Okere and Daramola, 2023). Ultimately, the practical application of accumulated knowledge translates ethical principles and research outputs into transparent governance structures and community-oriented initiatives (Ode and Ayavoo, 2020; Beltrán-Lizárraga et al., 2024).

Overall, developing KMC enables organisations to embed ethical, research-oriented and community-focused values into their strategic processes, thereby institutionalising socially responsible behaviour (Beltrán-Lizárraga et al., 2024; Sobaih et al., 2025). Integrating the KBV and Stakeholder perspectives (Grant, 1996; Freeman, 1984), this linkage represents a mechanism through which internal knowledge resources are transformed into external social value. In Kazakhstan, where national policies emphasise both digital transformation and societal impact (Ministry of Digital Development, 2017; Ministry of Education, 2024), this connection between KMC and ISR becomes particularly relevant. Accordingly,

H8. KMC is positively associated with ISR.

As GenAI improves KMC (Kudryavtsev, Khan and Kauttonen, 2024), it subsequently supports ISR by enhancing ethical governance, research integrity and community engagement (Beltrán-Lizárraga et al., 2024). Together, these knowledge-driven mechanisms create a sequential pathway through which AI-enabled innovation contributes to socially responsible and SP outcomes, consistent with the KBV (Grant, 1996). Thus,

H9. KMC and ISR serially mediate the relationship between GenAI use and SP.

Based on the hypotheses developed, a research model was constructed (Figure 1).

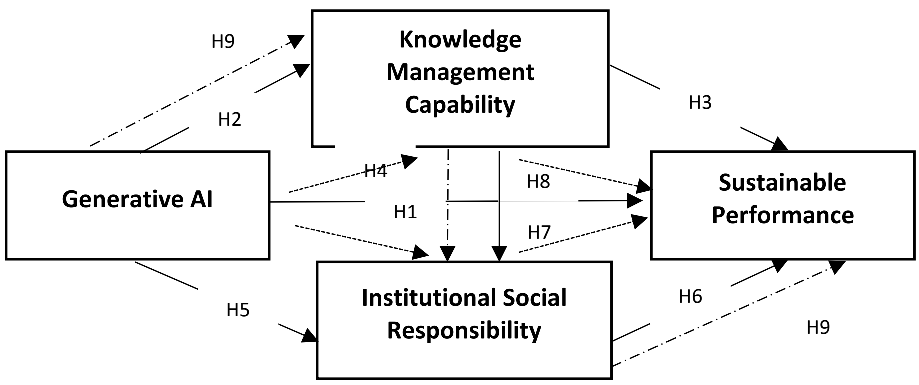

Figure 1: Research model

3. Research Methodology

This exploratory research aims to elucidate the impact of GenAI on the SP of HEI employees, with a specific focus on respondents who actively engage with GenAI tools as integral components of their daily routines. To achieve its primary goal and test the proposed hypotheses, this research employs a quantitative deductive method, which is considered the most efficient way to analyze the relationships between variables (Al-Qaysi et al., 2025).

3.1 Research Context

Kazakhstan was chosen as the context for this study. This choice is justified by several reasons. The country demonstrates a strong state commitment to digital transformation through initiatives such as 'Digital Kazakhstan' and national development plans that emphasize the integration of AI into key sectors, including education (Hamada et al., 2021; Ahmad et al., 2025). Although the AI market in the country is still developing, there is a recognized need to improve digital literacy and prepare a skilled workforce (Arapbayev, 2024; Zholdigaly, Zhumabayeva and Abdykerimova, 2024). This makes Kazakhstan a relevant 'transition economy' for studying how the adoption of GenAI impacts institutional performance and allows for obtaining timely, context-specific insights for policymakers and educators overseeing the country's technological integration.

3.2 Data Collection

The study was conducted in the Kostanay region, which hosts 34 colleges (27 public and seven private) according to the regional educational registry. Of these, 25 institutions participated in our survey, representing approximately 74% of the region's colleges. The data collection took place between January and February 2025. The survey was conducted among instructors from various academic disciplines, and the link to the online survey, created using Google Forms, was distributed via college administrations.

Participation in the survey was voluntary, with no monetary incentives offered, and participants were assured of the confidentiality and anonymity of their responses. Only teaching staff (full-time or part-time instructors with educational responsibilities) were eligible to participate, and respondents confirmed their employment status within the participating institutions. The questionnaire was initially developed in English and translated into Kazakh and Russian using a back-translation procedure to ensure conceptual equivalence. Respondents completed the survey in the language they found most comfortable. Attention-check items (e.g., entering a specific number) were included to ensure data quality.

A total of 483 responses were collected. After removing incomplete, duplicate, or low-quality submissions based on attention-check performance, 387 valid questionnaires were retained for data analysis. Since the exact number of distributed invitations could not be tracked, a formal survey response rate cannot be precisely calculated; therefore, 80.1% reflects the share of valid responses among those received, not a conventional response rate. The final sample size (n = 387) exceeds the minimum threshold required for PLS-SEM based on the 10× rule (Hair et al., 2019; Hair et al., 2021), confirming adequate statistical power. The demographic characteristics are presented in Table 1.

Table 1: Demographic Characteristics

Demographic Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Women	296	76.5%
	Men	91	23.5%
Age Group	20-29 years	43	11.1%
	30-39 years	85	22.0%
	40-49 years	98	25.3%
	50-59 years	112	28.9%
	60+ years	49	12.7%
Education Level	Higher Education	316	81.7%
	Master's Degree	62	16.0%
	Specialized Secondary Education	9	2.3%
Total		387	100.0%

3.3 Measures

To measure the research constructs, scales were adapted from existing literature. Participants were asked to express their level of agreement with the statements on a five-point Likert scale, ranging from (1) "Strongly

Disagree” to (5) “Strongly Agree”. The sources of the measurement instruments and their items are presented in Table 2, while the complete list of items is provided in Appendix A.

SmartPLS 4 was used for data analysis following the recommended two-step procedure: measurement model assessment followed by structural model evaluation (Hair et al., 2019).

Table 2: Source of measurement and items

Construct	Dimension	Items	Source
Generative AI Use		**3**	**Al-Emran, M., et al., 2025**
Sustainable Performance	Environmental Performance	3	Dey, M., et al., 2022
	Financial Performance	3	
	Social Performance	2	
Knowledge Management Capability	Knowledge Acquisition	4	The Dimensions of KMC Aboelmaged, M. G.,2014
	Knowledge Sharing	4	
	Knowledge Application	4	Items / Questions of KMC Masa'deh, R., et al., 2017
Institutional Social Responsibility	Ethical Responsibilities	7	Latif, K. F., et al., 2021
	Research and Development Responsibilities	4	
	Philanthropic Responsibilities	5	

Source(s): Authors’ work

4. Results

Data analysis was conducted using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method with SmartPLS 4 software. Following the recommended two-stage approach, the measurement model was assessed first, followed by the structural model (Hair et al., 2019).

4.1 Measurement Model Assessment

The adequacy of the measurement model was confirmed by evaluating its internal consistency reliability, convergent validity, and discriminant validity. Internal consistency was established, as all Cronbach’s Alpha (CA) and Composite Reliability (CR) values exceeded the 0.60 threshold (Table 3) (Hair et al., 2019). Initially, four items (KSH1, KAP1, ER3, and PR1) were removed due to weak factor loadings. Convergent validity was affirmed, with all item loadings and Average Variance Extracted (AVE) values for each construct being above 0.50 (Table 3). Finally, discriminant validity was supported through two criteria: the Fornell-Larcker criterion, where the square root of each construct's AVE was greater than its correlation with other constructs (Table 4), and the Heterotrait-Monotrait (HTMT) ratio, with all values falling below the conservative 0.9 threshold (Table 5) (Henseler et al., 2015). Collectively, these results confirm the measurement model's robustness, allowing for the subsequent structural model evaluation.

Table 3: Factor Loadings, Reliability and Convergent Validity

Items	Items	Loadings		α	CR	AVE
Generative AI use	AI1	0.914	AI	0.824	0.886	0.737
	AI2	0.842				
	AI3	0.816				
Knowledge Management Capability	KAC1	0.857	KAC	0.904	0.905	0.777
	KAC2	0.903				
	KAC3	0.896				
	KAC4	0.869				
	KSH2	0.872	KSH	0.871	0.871	0.795

Items	Items	Loadings		α	CR	AVE
	KSH3	0.902				
	KSH4	0.900				
	KAP2	0.819	KAP	0.879	0.900	0.807
	KAP3	0.940				
	KAP4	0.930				
Institution Social Responsibility	ER1	0.697	ER	0.847	0.851	0.567
	ER2	0.761				
	ER4	0.770				
	ER5	0.783				
	ER6	0.698				
	ER7	0.801				
	RDR1	0.741	RDR	0.867	0.878	0.717
	RDR2	0.873				
	RDR3	0.876				
	RDR4	0.887				
	PR2	0.623	PR	0.671	0.688	0.502
	PR3	0.726				
	PR4	0.794				
	PR5	0.682				
Sustainable Performance	EP1	0.814	EP	0.806	0.809	0.721
	EP2	0.880				
	EP3	0.851				
	FP1	0.843	FP	0.782	0.783	0.697
	FP2	0.848				
	FP3	0.813				
	ScP1	0.928	ScP	0.851	0.853	0.870
	ScP2	0.937				
Note(s): α: Cronbach alpha, CR: Composite reliability and AVE: Average variance extracted						

Source(s): Authors' work

Table 4: Discriminant Validity (Fornell and Larcker criterion)

	AI	KAC	KSH	KAP	ER	RDR	PR	EP	FP	ScP
AI	0.858									
KAC	0.109	0.882								
KSH	0.146	0.788	0.891							
KAP	0.193	0.778	0.782	0.898						
ER	0.147	0.637	0.681	0.646	0.776					
RDR	0.152	0.681	0.666	0.701	0.753	0.847				
PR	0.185	0.541	0.576	0.553	0.568	0.582	0.709			

	AI	KAC	KSH	KAP	ER	RDR	PR	EP	FP	ScP
EP	0.107	0.499	0.474	0.531	0.489	0.537	0.483	0.849		
FP	0.211	0.594	0.589	0.615	0.535	0.581	0.504	0.563	0.835	
ScP	0.104	0.693	0.686	0.654	0.689	0.659	0.475	0.495	0.606	0.933

Table 5: Discriminant validity (HTMT)

	AI	KAC	KSH	KAP	ER	RDR	PR	EP	FP	ScP
AI										
KAC	0.118									
KSH	0.162	0.888								
KAP	0.218	0.864	0.886							
ER	0.163	0.723	0.791	0.737						
RDR	0.167	0.768	0.765	0.792	0.899					
PR	0.238	0.677	0.741	0.694	0.732	0.751				
EP	0.132	0.583	0.566	0.630	0.582	0.638	0.640			
FP	0.256	0.706	0.713	0.733	0.653	0.704	0.686	0.707		
ScP	0.109	0.789	0.796	0.748	0.808	0.762	0.608	0.596	0.744	

4.2 Assessment of Higher-Order Constructs

The research model includes three formative higher-order constructs (HOCs): ISR, KMC, and SP. A standard two-step procedure was used to validate these HOCs. First, the Variance Inflation Factor (VIF) for each set of lower-order constructs (LOCs) was analyzed to check for multicollinearity. As shown in Table 7, all VIF values are below the recommended threshold of 5, indicating no multicollinearity issues (Hair et al., 2019).

Second, the relevance and statistical significance of the indicators were assessed by analyzing their outer weights and loadings. The results in Table 6 demonstrate that all outer weights are significant ($p < 0.001$) and all outer loadings are above the 0.70 threshold. Since all validation criteria are met, the HOCs (ISR, KMC, and SP) are confirmed as valid for the subsequent analysis (Sarstedt et al., 2019).

Table 6: Higher-order constructs

HOC	LOC	VIF	Outer weights	T	p value	Outer loadings	T	p value
KMC	KAC	3.204	0.324	4.170	0.000	0.917	40.749	0.000
	KSH	3.262	0.358	4.361	0.000	0.926	49.868	0.000
	KAP	3.134	0.399	6.137	0.000	0.931	59.542	0.000
ISR	ER	2.655	0.394	5.420	0.000	0.912	39.103	0.000
	RDR	2.721	0.486	6.245	0.000	0.936	47.433	0.000
	PR	1.594	0.247	4.255	0.000	0.754	18.479	0.000
SP	EP	1.552	0.234	4.010	0.000	0.718	13.584	0.000
	FP	1.850	0.307	4.836	0.000	0.818	25.072	0.000
	ScP	1.671	0.626	11.795	0.000	0.928	43.828	0.000
Note(s): LOC: Lower-order constructs, VIF: Variance inflation factor, t = t-statistics and p=probability								

Source(s): Authors' work

4.3 Structural Model Assessment

After confirming the measurement model's validity, the structural model was evaluated. First, collinearity among predictors was checked using the Variance Inflation Factor (VIF); all values were below the threshold of 5. Next, the model's explanatory and predictive power was assessed. As shown in Table 7, the R^2 values for ISR

(0.622) and SP (0.674) indicate substantial explanatory power, while the value for KMC (0.028) indicates weak explanatory power (Hair et al., 2019). The predictive relevance of the model was confirmed, as all Q^2 values were greater than zero (Hair et al., 2019).

Table 7: Explanatory and Predictive Power of the Model

Endogenous Construct	R^2	Q^2
KMC	0.028	0.021
ISR	0.622	0.025
SP	0.674	0.016

A bootstrapping procedure (10,000 samples) was used to test the hypotheses. In addition to path coefficients (β) and their significance (p-values), the effect size (f^2) was assessed for each direct path. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively.

Figure 2 illustrates the revised structural model with standardized path coefficients and R^2 values for endogenous constructs.

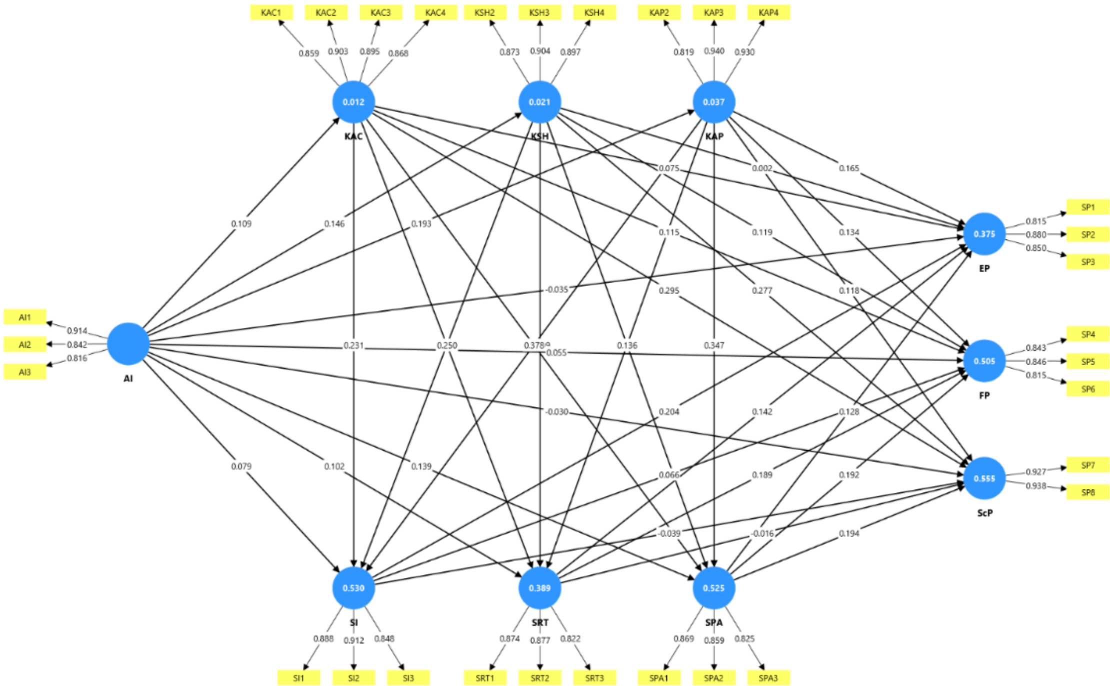

Figure 2: Structural model at the lower-order construct level

To provide a clearer overview of the latent-level relationships, Figure 3 illustrates a simplified structural model based on latent-variable scores. This visualization highlights the core causal links among GenAI, KMC, ISR, and SP.

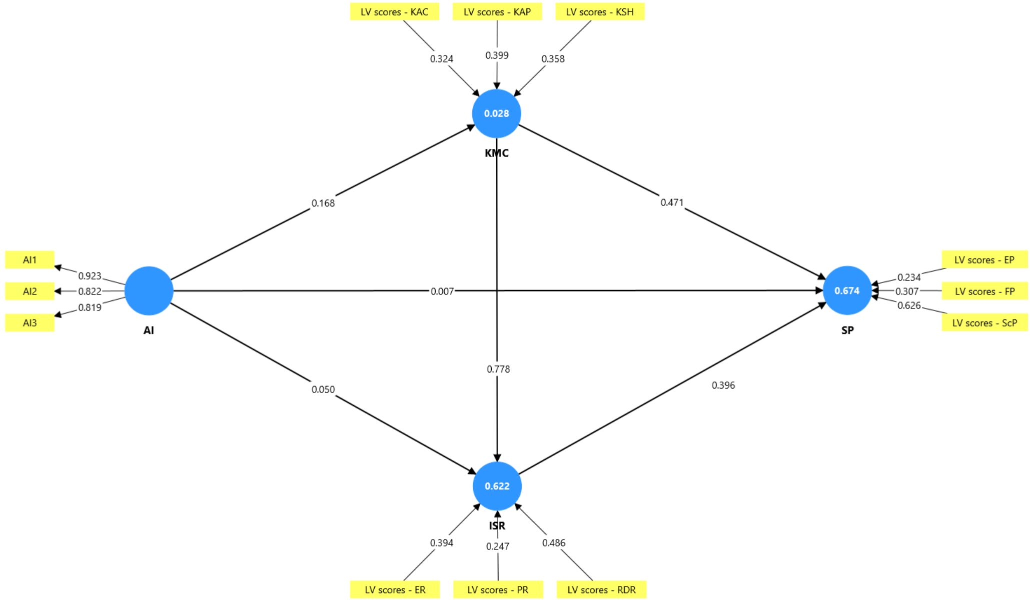

Figure 3: Structural model at the higher-order construct level

The structural model results are presented in Table 8.

Table 8:Results of Direct Hypothesis Testing

Hypothesis	Path Type	Path	β	T-Statistics	P-Values	f² Effect Size	Decision
H1	Direct	AI → SP	0.007	0.218	0.828	0.000	Not Supported
H2	Direct	AI → KMC	0.168	3.494	0.000	0.029	Supported
H3	Direct	KMC → SP	0.471	6.747	0.000	0.259	Supported
H5	Direct	AI → ISR	0.050	1.488	0.137	0.007	Not Supported
H6	Direct	ISR → SP	0.396	6.452	0.000	0.182	Supported
H8	Direct	KMC → ISR	0.778	20.029	0.000	1.556	Supported

The hypothesis testing indicates the following direct effects:

H1 (AI → SP): Not supported (β = 0.007, t = 0.218, p = 0.828).

H2 (AI → KMC): Supported (β = 0.168, t = 3.494, p < 0.001).

H3 (KMC → SP): Supported (β = 0.471, t = 6.747, p < 0.001).

H5 (AI → ISR): Not supported (β = 0.050, t = 1.488, p = 0.137).

H6 (ISR → SP): Supported (β = 0.396, t = 6.452, p < 0.001).

4.4 Mediation Analysis

Table 9 summarizes the indirect effects for H4, H7, and H9. The mediation analysis yielded the following results:

Table 9: Mediation Analysis Results

Hypothesis	Path Type	Path	β	T-Statistics	P-Values	Decision
H4	Indirect	AI → KMC → SP	0.079	3.116	0.002	Supported
H7	Indirect	AI → ISR → SP	0.020	1.389	0.165	Not Supported
H9	Indirect	AI → KMC → ISR → SP	0.052	2.801	0.005	Supported

H4 (AI → KMC → SP): Supported (β = 0.079, t = 3.116, p = 0.002)

H7 (AI → ISR → SP): Not supported (β = 0.020, t = 1.389, p = 0.165)

H9 (AI → KMC → ISR → SP): Supported (β = 0.052, t = 2.801, p = 0.005)

5. Discussion

5.1 Discussion of Findings

The findings provide a nuanced understanding of how GenAI use relates to SP in HEIs, particularly within the transition context of Kazakhstan. Although prior studies highlight GenAI's sustainability potential (Humble and Mozelius, 2024; Khan, Mehmood and Kwan, 2024), the lack of support for **H1** indicates that technological adoption alone does not directly enhance overall sustainable performance.

Rather than contradicting the RBV, this result illustrates its conditional logic. RBV suggests that performance gains emerge when valuable resources are supported by complementary capabilities that render them valuable, rare, inimitable, and non-substitutable (Barney, 1991). While GenAI may constitute a valuable technological asset, its strategic impact depends on institutional readiness, infrastructure, and human capital. In Kazakhstani HEIs, uneven digital maturity, limited AI integration, and insufficient faculty preparedness constrain the ability to convert GenAI use into sustained performance gains (Jamanbalayeva et al., 2025; Gafu et al., 2025). Without complementary governance and capability development, GenAI does not fulfil VRIN conditions, explaining the absence of a direct GenAI–SP relationship.

The supported relationships underlying **H2, H3, and H4** reposition KMC as the central conversion mechanism. The positive GenAI→KMC link (H2) aligns with the KBV, which conceptualises knowledge as a primary strategic resource (Grant, 1996). In practice, GenAI supports multilingual content management and academic information processing in Kazakhstani colleges (Sagimbayeva, 2024), strengthening knowledge acquisition, sharing, and application.

The strong KMC→SP relationship (H3) demonstrates that sustainability outcomes are driven less by technological presence than by enhanced knowledge processes. Effective knowledge utilisation improves innovation, operational efficiency, and resource optimisation, particularly in resource-constrained systems (Javed et al., 2025). The significant mediation effect (**H4**) confirms that GenAI contributes to SP indirectly by reinforcing knowledge-based capabilities that translate information into strategic and sustainability outcomes (Di Vaio et al., 2021). Thus, digital innovation precedes performance benefits through capability development rather than direct technological impact.

The results concerning institutional social responsibility (ISR) provide additional refinement. While ISR significantly enhances SP (**H6**), the non-significant GenAI→ISR relationship (**H5**) and the absence of mediation via ISR alone (**H7**) indicate that responsibility structures do not automatically emerge from technological adoption. GenAI is frequently implemented to improve productivity and efficiency (Janssen, 2025; Hosseini, Gao, and Vivas-Valencia, 2025), whereas ISR requires formal governance mechanisms and stakeholder-oriented accountability (Kong, 2024; Shen and Badulescu, 2025). In Kazakhstani HEIs, GenAI remains largely operational, focused on instructional and administrative support rather than strategic responsibility integration.

The significant ISR–SP link confirms Stakeholder Theory (Freeman, 1984), demonstrating that stakeholder-oriented governance strengthens institutional trust and long-term performance (Latif et al., 2024; Moussa, 2022). However, the absence of a direct GenAI→ISR pathway suggests that technological innovation does not inherently generate socially responsible governance without deliberate institutionalisation.

The confirmation of **H8 and H9** establishes a serial capability pathway (GenAI → KMC → ISR → SP). The strong KMC→ISR relationship (**H8**) indicates that effective knowledge processes facilitate responsibility integration (Beltrán-Lizárraga et al., 2024; Krawczyk, 2022). The supported serial mediation (H9) demonstrates that GenAI enhances sustainable performance through layered organisational mechanisms: strengthening knowledge capability first, enabling responsibility institutionalisation second, and improving sustainability outcomes third.

Taken together, the findings suggest that in transition HE systems such as Kazakhstan, the adoption of GenAI follows a capability maturation trajectory. Technological experimentation precedes consolidation of knowledge processes and subsequent embedding of responsibility structures. SP improvements materialise only when these organisational capabilities operate in combination, positioning KMC and ISR as complementary drivers that convert AI-enabled innovation into tangible sustainability outcomes (Kaldybay et al., 2024; Rakhmetullina et al., 2024).

5.2 Theoretical Contributions

This study advances the emerging literature on GenAI and SP in HE by explaining the organisational mechanisms through which GenAI contributes to SP. While prior research largely focuses on GenAI adoption, user perceptions, or educational outcomes (Al-Emran et al., 2025; Al-Qaysi et al., 2025; Nikolopoulou, 2025), limited evidence explains how GenAI translates into sustainability outcomes at the institutional level. By showing that GenAI does not directly influence SP but operates through organisational capabilities, this study clarifies the mechanisms linking AI adoption with sustainability outcomes in HEIs.

Second, the findings extend the KBV by identifying KMC as the key mechanism through which GenAI creates organisational value. While previous studies typically position knowledge-related factors as antecedents of AI adoption, the results demonstrate the reverse pathway, showing that GenAI strengthens KMC, which subsequently improves SP.

Finally, the study contributes to research on ISR in HE. By identifying a sequential pathway (GenAI → KMC → ISR → SP), the study integrates RBV, KBV, and Stakeholder Theory and demonstrates how digital technologies generate SP through layered organisational capabilities.

5.3 Practical Implications

The results show that GenAI delivers sustainability benefits only when supported by strong organisational capabilities. HEIs should prioritise capability-driven GenAI adoption by strengthening KM processes, digital skills and cross-unit collaboration. ISR likewise requires clearer governance, transparency procedures and responsible AI policies to ensure that GenAI enhances ethical conduct, research integrity and community engagement.

These implications are particularly significant for Kazakhstan, where uneven digital maturity, limited KM infrastructures and weak responsibility structures constrain the impact of technological innovation. Strengthening KMC and formalising ISR can help Kazakhstani universities convert GenAI use into broader sustainability benefits. For policymakers, investing in KM systems, AI ethics governance and incentives for socially oriented university practices will better align the sector with global sustainability and digital-transformation priorities.

5.4 Limitations and Future Research Directions

This study is limited by its cross-sectional design and non-probability sampling, which may affect causal interpretation and generalisability. Future research should employ stratified or multi-stage random sampling across diverse HEIs to ensure representation of academic disciplines, faculty ranks and institutional types. Conducting an a priori power analysis would help determine an adequate sample size, while two-wave or longitudinal data collection could reduce common method bias and capture temporal dynamics. Expanding geographical coverage and documenting sampling procedures, non-response patterns and regional differences in digital infrastructure would further strengthen methodological rigor. Comparative and cross-country studies could also illuminate how GenAI-enabled capabilities and responsibility structures evolve across different HE systems.

6. Conclusion

This study examined how GenAI contributes to the SP of HEIs through the mediating roles of KMC and ISR. The findings show that GenAI does not directly enhance SP, but instead operates through strengthened knowledge processes and, sequentially, through social responsibility structures. This confirms that technological adoption only generates value when embedded in robust organisational capabilities, extending the RBV and KBV perspectives in the HE context.

KMC emerged as a consistent and powerful enabler of both ISR and SP, highlighting its centrality for HEIs seeking to translate GenAI adoption into SP. The supported serial mediation further demonstrates that GenAI acquires strategic value only when HEIs combine effective knowledge processes with responsible governance and stakeholder-oriented practices. These findings are especially relevant for emerging systems such as Kazakhstan, where uneven digital maturity, fragmented responsibility structures and weak KM infrastructures remain key barriers to sustainability-oriented transformation.

Overall, this research provides new empirical evidence on how AI-enabled capabilities shape sustainability in HE and offers actionable insights for policymakers and university leaders seeking to align GenAI adoption with long-term development goals.

Ethical Statement: The Declaration of Helsinki was followed in conducting the study, and the protocol was approved by the Ethics Committee of Akhmet Baitursynuly Kostanay Regional University (Approval No. 25-B/2024 on December 20, 2024).

Use of AI-Assisted Language Tools: The authors used grammar-checking software during editing to improve language clarity and readability. All conceptual development, theoretical framework construction, research design, data analysis, interpretation of findings, and critical synthesis originated from the authors' scholarly expertise through direct human authorship. Language-editing tools were used solely for grammatical refinement, not for generating conceptual content or analytical insights.

Conflict of Interest: The authors declare no conflict of interest.

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Appendix A

Generative AI Use	I frequently use Generative AI tools for my academic endeavours. I spend a lot of time working with Generative AI tools. I exert considerable effort toward understanding and using GenAI.
Knowledge Management Capability	The institution…
Knowledge Acquisition	…collects useful knowledge identified from various sources. …provides opportunities to ask for specific knowledge when needed. …shares information about existing knowledge within the organization. …allows colleagues to inquire about skills when they need to learn something.
Knowledge Sharing	…ensures that knowledge is readily accessible to educators who need it. …distributes timely reports with relevant information to educators. …provides libraries, resource centers, and other platforms to display and distribute knowledge. …organizes lectures, conferences, and training sessions to facilitate knowledge sharing.
Knowledge Application	…offers various methods for educators to further develop their knowledge. …has mechanisms to safeguard knowledge both inside and outside the organization. …applies knowledge to meet critical needs and efficiently connects knowledge sources for problem-solving. …utilizes various methods to analyze and evaluate knowledge, generating new insights for future use.
Institution Social Responsibility	The institution…
Ethical Responsibilities	…has a comprehensive code of conduct. …tries to perform in a manner consistent with expectations of societal and ethical norms. …has reduced consumption of scarce resources like Electricity/Water. …encourages its students/staff initiatives towards good environmental performance. …encourages its members to follow professional standards. …is committed to prevention of pollution on all major environmental aspects. …behaves with honesty, transparency and fairness in all its activities and relationships with others.
Research and Development Responsibilities	…arranges for links with industry to develop skills in students. …encourages and empowers students to undertake research that creates social and economic impact. …integrates values such as respecting individual and social rights when carrying out research. …encourages scientific research on social problems and knowledge generation.
Philanthropic Responsibilities	…consistently offers scholarships to those in need. …offers free education to support staff. …understands and offers more time for students to pay their fees if they are in financial difficulty. …offers financial support to employees/students for extra-curricular activities. …participates in voluntary charitable activities within their local community.
Sustainable Performance	The Institution has a/an…
Environmental Performance	… initiative to reduce, reuse, and recycle. …initiative to reduce the negative environmental impact of its activities. …policy to improve its energy efficiency.

Financial Performance	…competitive advantages in its growth and performance. …competitive advantage in cost saving and operational efficiency. …competitive advantage in the value it provides.
Social Performance	…policy to strive to be a responsible and ethical institution. …policy to uphold business ethics and integrity.