GenAI, Leadership, and Entrepreneurial Orientation: The Mediating Role of Knowledge Management Capability

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Abstract: This study examines how generative artificial intelligence use and knowledge-oriented leadership influence entrepreneurial orientation through the mediating role of knowledge management capability in postsecondary education institutions . Despite the growing interest in artificial intelligence and entrepreneurship, prior research has predominantly focused on individual-level outcomes, while the organizational mechanisms that translate technological and leadership inputs into entrepreneurial behavior remain insufficiently understood. Addressing this gap, the present study adopts a capability-based perspective grounded in the knowledge-based view. A quantitative research design was employed. Data were collected from 387 academic staff members across 25 colleges in Kazakhstan using a structured questionnaire. The proposed model was tested using partial least squares structural equation modeling (PLS-SEM), enabling the assessment of both direct and indirect relationships among the constructs. The results indicate that knowledge-oriented leadership exerts a strong positive effect on knowledge management capability, which in turn significantly enhances entrepreneurial orientation. Generative AI use demonstrates both a direct effect on entrepreneurial orientation and an indirect effect through knowledge management capability, suggesting a complementary mediation mechanism. The findings further reveal that the impact of GenAI is contingent upon its integration into organizational knowledge processes rather than its isolated or ad-hoc use. The study contributes to the literature by providing a capability-based explanation of how technological and leadership factors jointly shape entrepreneurial orientation at the organizational level. It extends prior research by moving beyond individual-level perspectives and highlighting the central role of knowledge management capability as a transformation mechanism. From a practical standpoint, the findings suggest that educational institutions should prioritize the development of structured knowledge processes and leadership practices that support knowledge sharing and application when implementing GenAI initiatives. Such an approach enhances the sustainability and consistency of entrepreneurial behavior within knowledge-intensive environments.

Keywords: Generative artificial intelligence use, Knowledge-oriented leadership, Knowledge management capability, Entrepreneurial orientation, Postsecondary education

1. Introduction

Postsecondary education (PSE) institutions increasingly face pressure to demonstrate entrepreneurial orientation (EO), reflected in innovativeness, proactiveness, and opportunity-seeking behavior that enables the translation of academic knowledge into societal and economic value. At the same time, the rapid diffusion of generative artificial intelligence (GenAI) is transforming how knowledge is created, accessed, and reused in organizational settings. Despite growing interest, the strategic implications of generative artificial intelligence for entrepreneurial orientation in PSE institutions remain insufficiently theorized and empirically fragmented.

Existing research has largely emphasized individual-level outcomes, including learning performance, self-efficacy, and entrepreneurial intentions, while paying limited attention to organizational-level mechanisms that enable dispersed insights to be translated into coordinated entrepreneurial action (Xie and Wang, 2025).

Recent reviews further note that the GenAI–entrepreneurship relationship lacks clear explanatory pathways, calling for studies that identify intermediate organizational capabilities rather than relying on direct-effect

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models (Pimentel and Veliz Palomino, 2025). In line with this concern, management scholars emphasize that although AI-related trust and governance issues are increasingly discussed, research still rarely specifies concrete organizational mechanisms through which AI use translates into strategic outcomes, underscoring the need for capability-centered explanations (Grabowska and Rzemieniak, 2025).

From a knowledge-based view, organizational outcomes depend not simply on the availability of knowledge but on the ability to coordinate knowledge acquisition, sharing, and application across organizational members (Grant, 1996; Adam et al., 2022). This perspective places leadership and knowledge routines at the center of entrepreneurial behavior. Empirical evidence shows that knowledge-oriented leadership (KOL) positively shapes knowledge management processes and entrepreneurial orientation, yet also indicates that knowledge processes do not automatically translate into performance outcomes across contexts, highlighting a missing conversion mechanism between enablers and strategic results (Latif et al., 2021; Shahzad et al., 2021).

Building on this logic, we position knowledge management capability (KMC) as the key organizational mechanism linking GenAI use and KOL to EO. Prior research conceptualizes KMC as an integrated capability combining knowledge processes and enabling infrastructures, through which organizations transform dispersed knowledge into coordinated action (Gold, Malhotra and Segars, 2001; Latif et al., 2021). Related studies demonstrate that leadership effects on innovation and openness frequently operate indirectly through knowledge process and infrastructure capabilities, underscoring the centrality of KMC in transmitting managerial influence to downstream outcomes (Shahzad et al., 2021; Riaz et al., 2025).

Accordingly, we argue that GenAI use and KOL strengthen EO primarily when they contribute to the development of KMC, rather than when GenAI remains ad-hoc technology use or leadership actions remain symbolic. GenAI may support opportunity exploration and experimentation, but its organizational value depends on whether AI-generated insights are systematically shared, interpreted, and embedded into organizational routines (Alavi, Leidner and Mousavi, 2024; Kirchner et al., 2025). Without such capability, early productivity gains risk remaining fragmented and short-lived.

Accordingly, the present study addresses the following research question: Through what organizational mechanism do GenAI use and knowledge-oriented leadership jointly shape entrepreneurial orientation in PSE institutions?

The purpose of this study is therefore to examine a capability-based model in which GenAI use and KOL influence entrepreneurial orientation directly and indirectly through knowledge management capability in PSE institutions. By empirically testing these relationships and mediation pathways, the study responds to recent calls to integrate GenAI into established knowledge-management frameworks (Alavi, Leidner and Mousavi, 2024) and to clarify how leadership-driven capability building translates into entrepreneurial strategic behavior in knowledge-intensive organizational contexts (Latif et al., 2021; Shahzad et al., 2021).

2. Literature Review and Hypotheses Development

This review establishes the conceptual basis for examining the relationships among GenAI use, KOL, KMC, and EO. Drawing on prior research in knowledge management and entrepreneurship, the review focuses on how technological and leadership-related factors shape organizational knowledge processes and entrepreneurial outcomes. Against this backdrop, the review is structured around (1) the effects of GenAI use on KMC and EO, (2) the effects of KOL on KMC and EO, and (3) the mediating role of KMC and relevant contingencies.

GenAI refers to a class of AI systems that enable the creation and recombination of knowledge artefacts beyond traditional analytical AI, thereby influencing how knowledge is produced and used in organizational contexts (Alavi, Leidner and Mousavi, 2024; Kudryavtsev, Khan and Kauttonen, 2024).

At the same time, existing research highlights important uncertainties surrounding GenAI use, as concerns related to knowledge quality, algorithmic overreliance, and reduced human interaction underscore the need for managerial oversight (Alavi, Leidner and Mousavi, 2024).

Accordingly, the present study conceptualizes GenAI in terms of GenAI use, focusing on individuals' engagement with generative tools in everyday knowledge-related activities, consistent with the approach adopted by Al-Emran et al. (2025).

KMC refers to an organization's ability to acquire, share, and apply knowledge through coordinated organizational processes and supporting infrastructure, drawing on the knowledge process perspective of Gold, Malhotra and Segars (2001) and the operationalization proposed by Aboelmaged (2014).

Conceptualized as an organizational capability rather than a set of isolated practices, KMC encompasses coordinated routines that enable knowledge to be embedded in decision-making and action, allowing firms in knowledge-intensive contexts to mobilize knowledge resources in a repeatable and scalable manner beyond individual initiatives (Gold, Malhotra and Segars, 2001).

Recent research suggests that KMC remains fundamentally human-centered even in AI-rich environments, as effective knowledge utilization continues to depend on managerial coordination, human judgment, and the integration of digital tools into established organizational routines. In the absence of such capability, however, digital technologies may fail to generate meaningful organizational value, as knowledge remains fragmented and insufficiently translated into informed managerial action (Gold, Malhotra and Segars, 2001; Jarrahi et al., 2023; Kudryavtsev, Khan and Kauttonen, 2024).

KOL refers to a leadership approach that emphasizes the creation, sharing, and application of knowledge by fostering learning, collaboration, and supportive knowledge infrastructures within organizations (Donate and Sánchez de Pablo, 2015). Leaders adopting a knowledge-oriented approach shape learning environments that facilitate knowledge diffusion, experimentation, and the integration of individual expertise into collective organizational routines (Chaithanapat et al., 2022).

Recent empirical studies further indicate that KOL plays a key enabling role in the development of knowledge-based organizational capabilities. By shaping organizational norms, values, and routines, knowledge-oriented leaders provide the structural foundation through which knowledge can be systematically mobilized and embedded in organizational processes (Chaithanapat et al., 2022; Riaz et al., 2025; González-Mohíno et al., 2024).

Entrepreneurship is commonly conceptualized as a multidimensional phenomenon encompassing innovation, risk-taking, and proactiveness (Miller, 1983), which later formed the conceptual foundation for the dominant three-dimensional understanding of entrepreneurial orientation. Building on this foundation, Covin and Slevin (1989) formalized EO as a strategic posture reflecting organizations' entrepreneurial behavior at the organizational level.

Importantly, recent research demonstrates that entrepreneurial orientation is not confined to profit-seeking firms. A systematic literature review by Stock and Erpf (2023) shows that EO is increasingly applied in nonprofit, public, and mission-driven organizations, where it functions as a strategic posture supporting organizational adaptability, proactive response to environmental constraints, and the effective mobilization of limited resources. In such contexts, EO supports forms of strategic renewal that are aligned with social value creation, rather than exclusively driven by commercial objectives.

Within the KBV, organizational capabilities develop through the coordinated use of knowledge resources, a process that is increasingly shaped by digital technologies embedded in everyday work practices (Grant, 1996; Alavi, Leidner and Mousavi, 2024).

GenAI use reflects individuals' active engagement with generative tools in knowledge-related tasks. Through this engagement, GenAI supports the core processes underlying KMC by enabling users to synthesize fragmented information, identify non-obvious patterns, and - in partnership with human actors - embed outputs into shared organizational practices (Jarrahi et al., 2023; Kudryavtsev, Khan and Kauttonen, 2024). Over time, such repeated engagement can consolidate dispersed knowledge into coherent representations that are collectively interpretable and actionable across organizational routines.

However, this relationship is contingent on organizational conditions. Jarrahi et al. (2023) caution that the value of AI for knowledge management lies not in technology alone, but in the accompanying people, infrastructure, and processes. Without adequate managerial oversight, AI use may foster cognitive complacency - an uncritical reliance on AI outputs that undermines the human judgment essential to effective knowledge management. Furthermore, Kudryavtsev, Khan and Kauttonen (2024) note that GenAI can reduce rather than enhance knowledge work effectiveness when applied without sufficient data quality controls or organizational readiness.

Building on the above discussion, the following hypothesis is proposed:

H1: GenAI use is positively associated with KMC

From a KBV, organizational behavior under uncertainty is shaped by how organizational members interpret and mobilize knowledge in decision-making processes, a dynamic increasingly influenced by advanced digital technologies (Grant, 1996; Adam et al., 2022).

GenAI use may influence EO by reshaping how organizational members explore opportunities and act under uncertainty. Specifically, GenAI supports innovativeness by enabling idea generation and organizational learning; it reinforces proactiveness through predictive analytics and real-time insights that allow anticipation of environmental shifts; and it facilitates more informed risk-related decision-making by synthesizing information and reducing cognitive uncertainty (Pimentel and Veliz Palomino, 2025). Taken together, these mechanisms suggest that regular engagement with generative tools can strengthen the behavioral dispositions underlying EO at the organizational level.

However, these effects are not uniform across contexts. Pimentel and Veliz Palomino (2025) caution that GenAI's contribution to innovativeness depends heavily on entrepreneurs' absorptive capacity and ethical safeguards, while its benefits for proactiveness are constrained by data biases and limited contextual understanding. These barriers suggest that GenAI may amplify EO in digitally capable organizations while producing uneven or negligible effects elsewhere.

Building on the above discussion, the following hypothesis is proposed:

H2: GenAI use is positively associated with EO

According to the KBV, knowledge resides primarily in individuals, making its coordination and integration within organizations a challenging task/

KOL addresses this by fostering learning-oriented norms, encouraging knowledge exchange, and guiding the effective use of knowledge in organizational activities, thereby shaping a supportive knowledge climate that facilitates acquisition, sharing, and application of knowledge (Shamim et al., 2019).

However, this relationship is not unconditional. Shahzad et al. (2021) found that KOL did not directly predict inbound open innovation, suggesting that its influence on knowledge outcomes depends on organizational and cultural context. Riaz et al. (2023) further showed that technological turbulence can weaken the link between knowledge management process capability and exploitative innovation, indicating that environmental conditions may disrupt the chain from KOL through KMC to innovation outcomes.

Based on this reasoning, the following hypothesis is proposed:

H3: KOL is positively associated with KMC

EO reflects organizational patterns of innovativeness, proactiveness, and risk-related decision-making (Miller, 1983), and its development depends on contexts that support learning and experimentation. By legitimizing experimentation and encouraging knowledge exchange, knowledge-oriented leaders reduce uncertainty surrounding novel initiatives and enable opportunity-oriented behavior (Donate and Sánchez de Pablo, 2015; González-Mohíno et al., 2024).

That said, this effect is not automatic. González-Mohíno et al. (2024) found that KOL did not directly reduce relationship conflict without supporting coordination mechanisms, and Riaz et al. (2025) showed that KOL's influence on innovation operates indirectly through knowledge management capabilities. This suggests that KOL's association with EO may depend on enabling organizational conditions — a relationship that remains empirically underexplored and that this study directly addresses.

Accordingly, the following hypothesis is proposed:

H4: KOL is positively associated with EO

From a KBV, knowledge acquisition, sharing, and application are linked to improved organizational responsiveness and performance (Ha et al., 2021). Yu et al. (2022) show that knowledge management positively predicts entrepreneurial orientation in IT-sector SMEs, and this effect is stronger when leaders have the educational capacity to interpret and mobilize knowledge effectively. Hernández-Linares et al. (2024) corroborate this finding in a broader context, demonstrating that knowledge-based dynamic capabilities — spanning sensing, learning, integrating, and coordinating - are positively associated with entrepreneurial orientation across over 1,000 Iberian SMEs.

Yet the relationship is not automatic. When knowledge processes become routinized over time, they risk generating what Leonard-Barton (1992) called core rigidities - patterns that reinforce existing routines rather than enabling new entrepreneurial action. The KMC → EO link, in other words, depends on whether knowledge is actively directed outward toward opportunities rather than inward toward protecting what already exists.

Accordingly, the following hypothesis is proposed:

H5: KMC is positively associated with EO

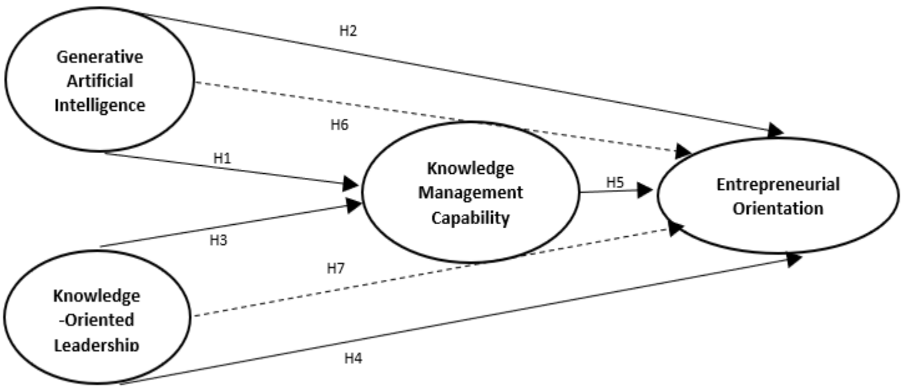
Having established that GenAI use and KOL each strengthen KMC (H1, H3), and that KMC in turn predicts EO (H5), it follows that KMC may serve as a mediating mechanism linking both antecedents to entrepreneurial orientation.

Building on the above discussion, the following hypotheses are proposed:

H6: KMC mediates the relationship between GenAI use and EO

H7: KMC mediates the relationship between KOL and EO

Taken together, the proposed hypotheses form the conceptual framework guiding this research. This framework, which illustrates the direct and mediated relationships between GenAI, KOL, KMC, and EO, is presented in Figure 1.



Source: Authors' own elaboration.

Figure 1: Conceptual framework and hypothesized relationships

3. Research Methodology

All constructs were measured on 5-point Likert scales (1 = "strongly disagree", 5 = "strongly agree").

- GenAI use - adapted from Al-Emran (2025) captured the frequency/extent of GenAI use in work routines (3 items).
- KOL - adapted from Donate and Sánchez de Pablo (2015) captured leadership behaviors (6 items).
- KMC - following Aboelmaged (2014), KMC was operationalized as a three-dimensional construct comprising knowledge acquisition - KAC (4 items), knowledge sharing – KSH (4 items), and knowledge application – KAP (4 items), with item content adapted from Masa'deh et al. (2017).
- EO - adapted from Covin and Slevin (1989) tradition, EO was conceptualized as three dimensions—innovativeness – INN (3 items), proactiveness – PRO (3 items), and risk-taking – RT (3 items).

All measurement items were contextually reworded for public sector educational institutions (colleges) while preserving the original content domain. The instrument underwent expert review and a small-scale pretest, after which minor wording adjustments were made for clarity. The resulting factor structures, as well as reliability and validity evidence, are reported in the measurement model results.

The complete list of measurement items and their sources is presented in Appendix A.

The participants in this study consisted of academic staff (teachers) from 25 colleges in Northern Kazakhstan, representing a broad range of disciplines. The participating institutions accounted for approximately 74% of all colleges in the Kostanay region (25 out of 34 colleges). Given that participation depended on institutional willingness to participate, a non-probability convenience sampling approach was employed.

Data were collected via an online questionnaire (Google Forms) administered between January and February 2025. Participation was voluntary; electronic informed consent was obtained before the survey began (see Ethical Statement); no monetary incentives were offered, and confidentiality and anonymity were assured.

Because the survey was distributed through institutional channels, the exact number of staff members who received the invitation could not be verified; therefore, a response rate was not calculated. In total, 483 questionnaires were received; after excluding outliers and straight-line responses, 387 valid questionnaires were retained for statistical analysis.

To assess indicator collinearity within the reflective measurement model, we inspected variance inflation factors (VIFs) for all indicators. All values were below the commonly used cutoff of 5.0 (range = 1.664–3.926), indicating no critical redundancy among items. Although two indicators (KAP3 = 3.926; KAP4 = 3.620) exceeded the stricter heuristic of 3.3, they remained well below 5.0 and were retained to preserve content coverage, consistent with recommended practice for reflective indicators (Hair et al., 2021).

Because all constructs were measured through a single self-administered questionnaire, common method bias was assessed using Harman's single-factor test. All 30 items were entered into an unrotated principal axis factor analysis with the number of factors constrained to one. The single factor accounted for 48.9% of the total variance, below the 50% threshold (Podsakoff et al., 2003), indicating that common method bias is unlikely to substantially distort the findings. This is further supported by procedural safeguards applied during data collection, including respondent anonymity and assurance of confidentiality.

Given the small effect size of the GenAI–KMC path ($\beta = 0.086$, $f^2 = 0.012$), a post-hoc power analysis was conducted ($N = 387$, $\alpha = 0.05$, two predictors). The achieved power was 0.58, below the conventional 0.80 threshold.

Because response rate could not be calculated, non-response bias was assessed by comparing early and late respondents (first and last thirds of the response distribution by submission time) on the study's key constructs. No significant differences were found (all $p > 0.10$), suggesting that non-response bias is unlikely to be a major concern.

4. Research Results

The measurement model was evaluated to confirm the constructs’ reliability and validity. Two

items (KAP1 and KSH1) were deleted from the data because of low factor loadings lower than the specified value of 0.50, all other items were included in the measuring model. As a result, all factor outer loadings in Table 1 are more than the recommended value of 0.50 (Hair et al., 2021).

The values of Cronbach’s alpha are more than the advised value of 0.70 (Hair et al., 2021). Moreover, CR values are also greater than the recommended threshold of 0.70 (Ringle et al., 2020). The next step was to test the convergent validity which was also established because the AVE values are equal to or greater than 0.50.

Reliability and validity results with factor loadings are presented in Table 1.

Further discriminant validity was assessed (Table 2). The square roots of AVE of the constructs are greater than the correlation of inter constructs. Moreover, discriminant validity was also examined with the heterotrait-monotrait ratio of correlation (Henseler, Ringle and Sarstedt, 2015) and the resulting values are less than the recommended value of 0.90. Hence, discriminant validity was established.

Table 1: Measurement model results

	Outer loadings	Cronbach alpha	CR	AVE
GenAI		0.824	0.884	0.737
GenAI1	0.913			
GenAI2	0.840			
GenAI3	0.818			
KOL		0.907	0.914	0.683
KOL1	0.873			
KOL2	0.847			
KOL3	0.784			
KOL4	0.817			
KOL5	0.861			

	Outer loadings	Cronbach alpha	CR	AVE
KOL6	0.772			
KAC		0.904	0.905	0.777
KAC1	0.858			
KAC2	0.903			
KAC3	0.896			
KAC4	0.869			
KSH		0.871	0.871	0.795
KSH2	0.873			
KSH3	0.902			
KSH4	0.899			
KAP		0.879	0.900	0.807
KAP2	0.819			
KAP3	0.940			
KAP4	0.930			
INN		0.858	0.864	0.779
INN1	0.889			
INN2	0.913			
INN3	0.845			
PRO		0.811	0.822	0.725
PRO1	0.868			
PRO2	0.858			
PRO3	0.828			
RT		0.821	0.826	0.736
RT1	0.869			
RT2	0.881			
RT3	0.822			

Source: Authors’ elaboration based on SmartPLS 4

Table 2: Discriminant validity (HTMT criterion)

	GenAI	KOL	KAC	KSH	KAP	INN	PRO	RT
GenAI								
KOL	0.121							
KAC	0.118	0.758						
KSH	0.162	0.781	0.888					
KAP	0.218	0.792	0.864	0.886				
INN	0.227	0.696	0.743	0.744	0.792			
PRO	0.308	0.759	0.746	0.739	0.790	0.864		
RT	0.236	0.672	0.656	0.638	0.683	0.796	0.894	

Source: Authors’ elaboration based on SmartPLS 4

To validate the higher-order formative constructs, multicollinearity among the lower-order dimensions was assessed using variance inflation factors (VIF). All VIF values were below the threshold of 5.0, indicating no collinearity concerns (Hair et al., 2021). The significance and relevance of outer weights were examined (Sarstedt et al., 2019), and all outer weights were statistically significant, while outer loadings were additionally inspected to assess the absolute contribution of each dimension. Overall, the results support the validity of the higher-order constructs (Table 3).

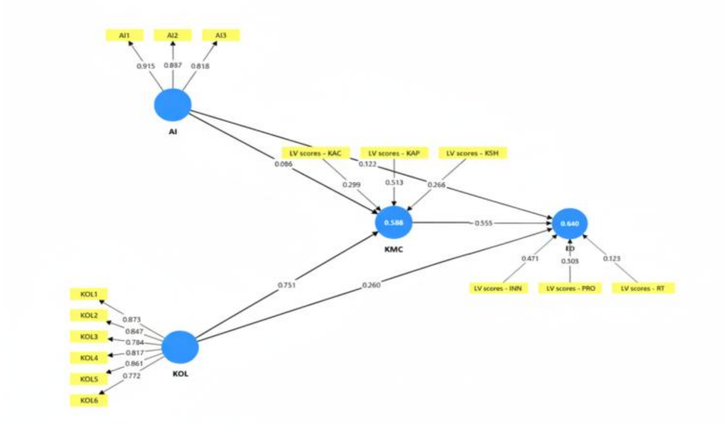
Table 3: Higher order construct validation

	VIF	Weights	Loadings
KAC → KMC	3.204	0.299	0.907
KSH → KMC	3.262	0.266	0.903
KAP → KMC	3.134	0.513	0.953
INN → EO	2.318	0.471	0.917
PRO → EO	2.728	0.503	0.933
RT → EO	2.367	0.123	0.807

Source: Authors' elaboration based on SmartPLS 4

The structural model (Figure 2) demonstrates the hypothesized paths in the research framework.

The structural model was assessed using standardized path coefficients (β) obtained via nonparametric bootstrapping with 10,000 resamples (two-tailed, 95% confidence intervals). Multicollinearity was examined using inner VIF values, all of which were below 5.0.



Source: Authors' elaboration based on SmartPLS 4

Figure 2: Structural model results with standardized path coefficients (β) and endogenous R^2 values (R^2_KMC = 0.586; R^2_EO = 0.640; SRMR = 0.046)

The model's explanatory power was evaluated using R^2 values exceeding the minimum threshold of 0.10 (Falk and Miller, 1992), while predictive relevance was confirmed by Q^2 values greater than zero (Table 4). Model fit was assessed using the standardized root mean square residual (SRMR = 0.046), indicating an acceptable fit (Hair et al., 2021).

Table 4: R^2 and Q^2

	R^2	Q^2
KMC	0.586	0.576
EO	0.640	0.500

Source: Authors' elaboration based on SmartPLS 4

Table 5 presents the structural path results. GenAI use has a positive and significant effect on KMC (β = 0.086, p = 0.013), supporting H1, and on EO (β = 0.122, p = 0.001), supporting H2. KOL shows a strong positive effect on KMC (β = 0.751, p < 0.001), confirming H3, and also positively influences EO (β = 0.260, p < 0.001), supporting H4. In addition, KMC is positively associated with EO (β = 0.555, p < 0.001), supporting H5.

Table 5: Hypothesis test results (structural paths)

Hypothesis Path	β (O)	STDEV	t-statistics	p-value	Decision
H1: GenAI → KMC	0.086	0.035	2.479	0.013	Supported
H2: GenAI → EO	0.122	0.035	3.450	0.001	Supported
H3: KOL → KMC	0.751	0.027	27.515	< 0.001	Supported
H4: KOL → EO	0.260	0.061	4.270	< 0.001	Supported
H5: KMC → EO	0.555	0.057	9.686	< 0.001	Supported

Source: Authors' elaboration based on SmartPLS 4

Mediation analysis based on bootstrapped indirect effects indicates that KMC partially mediates the relationship between GenAI use and EO (VAF = 28%), supporting H6. A substantial partial mediation is also observed between KOL and EO through KMC (VAF = 62%), supporting H7. Mediation results are reported in Table 6.

Table 6: Mediation analysis

Path (mediation)	β (O)	STDEV	t-statistics	p-value
GenAI → KMC → EO	0.048	0.020	2.416	0.016
KOL → KMC → EO	0.417	0.048	8.765	< 0.001

Source: Authors' elaboration based on SmartPLS 4

5. Discussion

The findings indicate that GenAI use and KOL jointly contribute to entrepreneurial orientation through their effects on knowledge management capability. All hypothesized relationships are positive and statistically significant, and the mediation results highlight the central role of KMC as the mechanism translating technological and leadership inputs into entrepreneurial behavior.

Regarding H1, the results indicate that GenAI use strengthens KMC by supporting knowledge access, interpretation, and reuse in everyday work activities, consistent with research on AI-enabled knowledge processes (Jarrahi et al., 2023; Kudryavtsev, Khan and Kauttonen, 2024). However, the modest effect size (β = 0.086) warrants closer examination. Two complementary explanations are plausible. First, the measurement of GenAI use in this study captures frequency of engagement rather than the quality or depth of integration into organizational routines. As Jarrahi et al. (2023) caution, the organizational value of AI for knowledge management depends not on technology alone but on the accompanying people, infrastructure, and processes — conditions that may vary considerably across institutions. Second, the institutional context likely plays a role. Government-led AI initiatives in Kazakhstan have traditionally prioritized the university sector over colleges; indicatively, the national AI-Sana programme targets students and faculty of higher education institutions, with no parallel provision for the PSE college system (Ministry of Science and Higher Education of the Republic of Kazakhstan, 2025).Under these conditions, GenAI use among college staff may remain largely informal and individually driven, limiting its capacity to strengthen collective knowledge management routines. Evidence from postsecondary education institutions in Kazakhstan further confirms that KMC serves as the central conversion mechanism through which GenAI generates organizational value, while GenAI alone does not directly enhance institutional performance (Amantayeva, Sartanova and Baizhanova , 2026).

With respect to H2, the results confirm that GenAI use directly strengthens EO across all three of its dimensions. For innovativeness, generative tools support idea generation and organizational learning, though this benefit is bounded by absorptive capacity and the availability of ethical safeguards (Pimentel and Veliz Palomino, 2025). For proactiveness, GenAI enables real-time synthesis of environmental signals, yet data biases and limited contextual understanding can distort rather than sharpen strategic foresight (Pimentel and Veliz Palomino, 2025). For risk-taking, GenAI reduces cognitive uncertainty by processing large volumes of data and generating evidence-based recommendations — provided that data quality and interpretive capabilities are adequate (López-Solís et al., 2025). Notably, part of this direct effect likely operates at the level of individual cognition rather than through collective knowledge routines: generative tools enable users to reframe problems and construct alternative scenarios in ways that shift strategic thinking dispositions independently of shared organizational processes.

In line with H3, KOL emerges as the primary driver of KMC (β = 0.751), substantially outpacing the effect of GenAI use (β = 0.086). This finding aligns with evidence showing that knowledge-oriented leaders strengthen KMC by motivating employees to create, share, and apply knowledge, by reinforcing this through reward structures and communication, and by shaping the cultural and structural infrastructure that embeds knowledge use into organizational routines (Shahzad et al., 2021; Riaz et al., 2025). Through these mechanisms, leadership translates individual knowledge into collective organizational capability.

In the PSE context, such practices may take the form of regular cross-departmental knowledge-sharing sessions, structured mentorship between experienced and early-career faculty, recognition systems that reward knowledge contributions, or institutionalized digital repositories consolidating pedagogical best practices.

The findings support H4 (β = 0.260, $p < 0.001$), confirming that KOL strengthens EO by fostering learning-oriented norms and guiding knowledge application in organizational activities. By legitimizing experimentation and reducing uncertainty surrounding novel initiatives, knowledge-oriented leaders create conditions under which opportunity-oriented behavior can emerge (Donate and Sánchez de Pablo, 2015; González-Mohíno et al., 2024). This suggests that in the PSE context, leadership influence on entrepreneurial behavior operates not only indirectly through KMC but also through the direct shaping of organizational norms that support innovativeness, proactiveness, and risk-taking.

The findings also support H5, confirming that KMC positively predicts EO. This is consistent with Hernández-Linares et al. (2024) and Yu et al. (2022), who report similar effects across SME contexts. The result suggests that colleges with stronger knowledge management routines are better positioned to recognize and act on emerging opportunities — because systematic knowledge acquisition and sharing reduce the uncertainty that typically inhibits proactive and risk-taking behavior. However, this effect is likely conditional: when knowledge processes become overly routinized, they may reinforce existing practices rather than stimulate new ones (Hernández-Linares et al., 2024; Leonard-Barton, 1992).

The findings support both H6 and H7, confirming the mediating role of KMC. For H6, KMC accounts for approximately 28% of the total effect of GenAI use on EO, suggesting that while GenAI exerts a direct influence on entrepreneurial behavior, a meaningful share of its effect operates through organizational knowledge processes. For H7, the mediating share is substantially larger (VAF ≈ 62%), indicating that KOL influences EO primarily through the knowledge management capability it develops — consistent with evidence that leadership effects on innovation-related outcomes operate indirectly through knowledge processes rather than through direct behavioral influence alone (Shahzad et al., 2021; Riaz et al., 2025).

An alternative explanation should also be considered: institutions with already strong EO may be more inclined to invest in GenAI and KM practices, rather than the reverse. The cross-sectional design of this study cannot rule out this possibility, and the observed relationships should be interpreted as associations rather than confirmed causal effects.

6. Conclusion

Returning to our central research question, the findings indicate that KMC is the key mechanism through which GenAI use and KOL jointly shape EO in PSE institutions.

This study examined how GenAI use and KOL influence EO through KMC in PSE institutions. The findings show that both technological and leadership-related factors contribute to EO, with KMC serving as the central mechanism through which these influences are translated into entrepreneurial behavior.

The results indicate that KOL affects EO primarily by strengthening KMC, whereas GenAI use operates through both direct and indirect pathways. This pattern suggests that entrepreneurial orientation is fostered not by isolated technology adoption or leadership actions, but by the development of organizational knowledge capability that enables systematic knowledge acquisition, sharing, and application.

From a theoretical perspective, this study contributes by clarifying a capability-based mechanism underlying entrepreneurial orientation. It demonstrates that leadership-driven KMC represents the key channel through which managerial intent and digital technologies are converted into coordinated organizational action. In addition, the findings extend emerging GenAI research by showing that AI-related effects on EO are more likely to persist when GenAI use is embedded within organizational knowledge structures rather than applied in an ad-hoc manner.

These findings challenge the prevailing assumption that GenAI adoption alone is sufficient to drive strategic outcomes, highlighting instead the enduring centrality of human-centered knowledge processes in converting technological inputs into entrepreneurial behavior.From a managerial perspective, the results highlight the importance of strengthening KMC before scaling GenAI initiatives. Leaders should focus on institutionalizing knowledge routines, shared repositories, and clear responsibility for knowledge validation, while reinforcing norms that encourage knowledge sharing and application. Such arrangements support the development of more consistent and sustainable entrepreneurial behaviors over time.

Therefore, before investing heavily in GenAI tools, educational leaders should first strengthen knowledge management routines — such as cross-departmental knowledge reviews, faculty mentorship programs, and structured pedagogical repositories. These arrangements form the organizational foundation upon which GenAI initiatives can generate sustainable entrepreneurial value.

This study has several limitations. The data were collected from colleges within a single national context, which may limit generalizability. The cross-sectional and self-reported design constrains causal inference. The post-hoc power for the GenAI–KMC path (0.58) suggests that larger samples are needed to reliably detect such small effects in future research. In addition, construct operationalization can be further refined, particularly with respect to measuring the quality and maturity of GenAI use rather than its intensity alone. Future research should replicate the model across different educational segments and national settings, adopt longitudinal and multi-source designs, and examine contextual boundary conditions that may shape the observed relationships.

Use of AI-Assisted Language Tools: The manuscript was proofread using grammar-checking tools to improve clarity and readability. All theoretical development, research design, data analysis, and interpretation were carried out independently by the authors. The tools were used solely for language editing and did not contribute to the conceptual or analytical content.

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).

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

Data Availability Statement: The data supporting this study are available from the corresponding author upon reasonable request.

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Appendix A

Generative AI Use	1. I frequently use Generative AI tools for my academic endeavours. 2. I spend a lot of time working with Generative AI tools. 3. I exert considerable effort toward understanding and using GenAI.
Knowledge Oriented Leadership	Over the last three years: 1. The Institution has been fostering an environment that encourages responsible behavior and teamwork. 2. The Institution has seen academic leadership (managers) take on the role of knowledge leaders, characterized by openness, tolerance of mistakes, and mediation to achieve institutional goals. 3.The Institution has managers who promote learning from experience while tolerating mistakes up to a certain point. 4.The Institution has managers who act as advisers, with controls serving primarily as an assessment of goal achievement. 5.The Institution has encouraged managers to facilitate the acquisition of external knowledge. 6. The Institution has rewarded employees who share and apply their knowledge.
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.
Entrepreneurial Orientation	
Innovativeness	1. Our institution actively supports the development and implementation of new ideas and innovative solutions. 2. Over recent years, our institution has introduced several new programs, initiatives, or organizational practices. 3.Changes implemented in our institution are typically substantial rather than minor or incremental.
Risk-taking	4. The management of our institution is willing to support initiatives that involve uncertainty and potential risk. 5. To achieve institutional development goals, our organization is prepared to pursue bold and unconventional actions. 6. When facing uncertainty, our institution prefers active decision-making rather than a wait-and-see approach.
Proactiveness	7. Our institution tends to initiate changes rather than merely respond to external developments. 8. Our institution is often among the first to implement new initiatives or managerial practices. 9. The management of our institution emphasizes proactive leadership and anticipatory development.

