

From Institutional Memory to Anticipatory Intelligence: Agentic AI in University Knowledge Management

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Abstract: Universities face increasing pressure not merely to archive past activity but to anticipate what is coming, as rankings, funding landscapes, and research priorities shift in response to forces no single institution can fully predict. Traditional knowledge management (KM) approaches, designed to preserve and retrieve institutional memory, answer yesterday's questions with yesterday's data. Agentic artificial intelligence (AI), distinguished by goal-directed autonomy, continuous environmental monitoring, and proactive recommendation generation, offers a qualitatively different proposition: a knowledge system that does not wait to be queried. This study investigates how agentic AI reshapes KM and research intelligence practices at the European University of Armenia, and whether those changes produce enhanced strategic foresight. Using an exploratory qualitative case study, data were gathered through semi-structured interviews with twelve purposively selected participants and triangulated against institutional documents. Thematic analysis following Braun and Clarke (2006), informed by the data-structure conventions of the Gioia methodology (Gioia, Corley and Hamilton 2013), was applied across both data sources, with findings organised around five research propositions. Agentic AI strengthens research intelligence by integrating siloed data streams, enabling real-time bibliometric monitoring, and generating predictive scenarios that inform leadership decisions. This intelligence does not directly produce strategic foresight; it must be interpreted and acted upon by human decision-makers, making research intelligence the indispensable intermediary. Gains in knowledge sharing were also evident, although participants cautioned that fluent AI summaries may erode the reflective dialogue through which academic communities validate knowledge. Governance quality, ethical frameworks, and the depth of human–AI collaboration emerged as equally critical conditions, operating as preconditions for value rather than safeguards added after deployment. The practical implication is that investment in agentic AI must be matched by investment in human interpretive capacity and governance infrastructure. The study contributes empirically to KM theory by showing how agentic AI repositions universities from passive custodians of recorded knowledge to active, intelligence-driven institutions, offers context-specific evidence from an emerging post-Soviet university, and provides guidance for responsible AI integration.

Keywords: Agentic AI, Knowledge management, Research intelligence, Strategic foresight, Higher education, Organisational learning

1. Introduction

Modern universities face a particular irony: institutions whose purpose is producing and disseminating knowledge often struggle to manage it for their own strategic benefit. Research outputs accumulate in siloed databases, funding intelligence arrives too late, and collaboration opportunities pass unnoticed. The very richness of the surrounding data environment becomes a source of paralysis rather than power when no coherent mechanism transforms it into actionable intelligence.

KM in higher education has historically addressed this challenge through archival and retrieval logic: building better repositories, improving information accessibility, and documenting institutional processes (Rowley 2000; Kidwell et al. 2000). These are worthy ambitions, and they reflect the foundational insight that knowledge constitutes a primary strategic asset for universities (Drucker 1993; Nonaka and Takeuchi 1995). Repository logic is, however, fundamentally retrospective. It captures what has already been learned rather than anticipating what must be known next.

Senge's (1990) concept of the learning organisation gestures toward something more dynamic: institutions that develop adaptive capacity, sense environmental shifts early, and respond with intelligence rather than inertia. Strategic foresight, the disciplined practice of exploring alternative futures to inform present decisions, has emerged as the operational expression of this ideal (Rohrbeck and Kum 2018). Yet the gap between foresight as aspiration and as practice remains wide for most universities, which rely on retrospective metrics long after those metrics have ceased to reflect their operating environment.

Agentic AI, systems that do not simply respond to queries but actively monitor, learn, and generate recommendations without being prompted, offers a qualitatively different proposition (Kshetri 2025). The research was conducted at the European University of Armenia and is guided by a single overarching question:

How does the integration of agentic AI influence knowledge management and strategic foresight capabilities in a higher education institution? Because the phenomenon is novel and the study exploratory, the inquiry does not begin from pre-specified hypotheses. Instead, five research propositions are developed from the literature and presented at the close of the review (Section 2.7), where they emerge from the conceptual argument rather than preceding it, and then scaffold the empirical work that follows.

2. Literature Review

2.1 Knowledge Management in Higher Education: The Repository Trap

KM entered the organisational literature with a compelling argument: competitive advantage would accrue to those who could most effectively create, share, and exploit knowledge (Nonaka and Takeuchi 1995; Grant 1996). Universities seemed natural beneficiaries, yet adoption has been uneven. Rowley (2000) observed that universities are structurally ill-suited to corporate KM models: decentralised, governed by academic autonomy, fragmented across disciplinary silos, and resistant to top-down codification. The result is the repository trap: universities invest in systems that capture knowledge effectively but do little strategically useful with it. A repository-driven model defines knowledge as a thing to be stored rather than a capacity to be developed; it cannot, by design, generate anticipatory intelligence.

2.2 Learning Organisations, Strategic Foresight, and an Inconvenient Tension

Senge's (1990) learning organisation offers the vocabulary for this transition: adaptive systems, shared mental models, and systemic thinking point toward institutions capable of shaping their response to change before it fully arrives. Strategic foresight operationalises this capacity, providing structured methods for scanning emerging trends, constructing alternative scenarios, and anchoring present decisions to plausible futures (Rohrbeck and Kum 2018). The tension AI introduces is worth naming. Learning organisation theory is fundamentally humanist, placing reflective dialogue and collective sensemaking at the heart of organisational intelligence; strategic foresight powered by agentic AI is, by contrast, algorithmic, deriving intelligence from pattern recognition across vast datasets rather than human conversation. Whether the two can be genuinely complementary is an open question this study takes up directly.

2.3 Research Intelligence: Potential Unrealised

Research intelligence, the systematic collection and interpretation of bibliometric data, funding trends, collaboration networks, and impact indicators to inform strategy, represents KM's most direct contribution to competitive positioning. Recent work reframes business intelligence and analytics as a means of creating and disseminating organisational knowledge rather than merely reporting it (Lasca et al. 2026), and links such intelligence capabilities to strategic performance under conditions of environmental uncertainty (Vo et al. 2026). In principle, research intelligence transforms raw data into the forward-looking knowledge that Teece's (2007) dynamic capabilities framework identifies as essential: sensing opportunities, seizing them, and reconfiguring resources accordingly. In practice, most operations are understaffed, reliant on manual processes, and oriented toward reporting rather than forecasting, a gap that agentic AI is well positioned to address.

2.4 Artificial Intelligence in Knowledge Management: Useful but Insufficient

Natural language processing, machine learning classifiers, recommendation engines, and semantic search tools have been integrated into organisational knowledge systems for over a decade. In higher education, AI has been deployed in learning analytics, plagiarism detection, citation management, and administrative automation (Davenport and Ronanki 2018; Luckin et al. 2016). The arrival of generative AI has intensified scholarly attention: Alavi, Leidner and Mousavi (2024) argue that generative systems reconfigure the core KM processes of knowledge creation, storage, transfer, and application, while cautioning that they may marginalise junior knowledge workers and erode the social processes through which knowledge is validated. Yet most deployed applications share a common limitation: they are reactive, returning outputs calibrated to queries already asked. Governance concerns also apply: algorithmic opacity obscures why a system produces a given recommendation, and bias in training data can systematically disadvantage certain research communities (Papagiannidis, Mikalef and Conboy 2025).

2.5 Agentic AI: A Different Animal

Agentic AI departs from the reactive, query–response model. Its defining characteristic is autonomy: an agentic system pursues goals, monitors its environment continuously, learns without human instruction, and generates recommendations proactively (Kshetri 2025). Where a conventional tool waits to be asked whether a funding

call is relevant, an agentic system identifies the call, assesses it against strategic priorities, flags it to the appropriate decision-maker, and begins modelling the implications of a successful application. Theoretically, this repositions AI from instrument to actor: knowledge creation, once conceptualised as exclusively human (Nonaka and Takeuchi 1995), becomes distributed across human and machine agents, and the passive repository gives way to something resembling an institutional nervous system that continuously senses, interprets, and alerts. Despite the significance of this shift, and the accelerating adoption of agentic systems across higher education (Kshetri 2025; Aguado-García, Alonso-Muñoz and De-Pablos-Heredero 2025), empirical research on agentic AI as a knowledge actor within universities remains scarce.

2.6 Governance and the Conditions for Trust

The autonomy that distinguishes agentic AI also raises its governance stakes. Because agentic systems act on their environment rather than merely describing it, accountability, transparency, and bias acquire an operational rather than a purely ethical character. Papagiannidis, Mikalef and Conboy (2025) frame responsible AI governance as a configuration of structural, relational, and procedural practices that together determine whether AI outputs are treated as trustworthy. In higher education, where decisions carry reputational and academic weight, the same system may be a credible strategic instrument in one governance environment and an ignored liability in another. Governance, on this view, is not a constraint imposed after the fact but a precondition for value.

2.7 From Literature to Propositions

Taken together, the literature surfaces five gaps: the theoretical divide between KM as repository management and KM as anticipatory capability; the absence of empirical studies of agentic AI as an autonomous knowledge actor in universities; the insufficient integration of research intelligence scholarship with learning organisation theory; the underexplored governance and ethical dimensions of AI-enabled foresight; and the scarcity of context-specific evidence from Eastern European and post-Soviet institutions. From these gaps and the argument developed above, five research propositions are derived. Consistent with the study's exploratory qualitative design, these are framed as propositions to be explored rather than hypotheses to be tested: they articulate theoretically informed expectations about processes and relationships, assessed against the interpretive weight of the evidence rather than through statistical inference.

- **P1:** Agentic AI strengthens research intelligence capabilities within the university, shifting them from a retrospective to an anticipatory orientation.
- **P2:** Enhanced research intelligence capabilities contribute to strategic foresight in institutional decision-making.
- **P3:** Agentic AI strengthens knowledge creation and sharing processes, while simultaneously placing the deliberative dimension of those processes at risk.
- **P4:** Agentic AI informs strategic foresight only indirectly, through research intelligence interpreted by human decision-makers.
- **P5:** Governance quality and human–AI collaboration condition the extent to which agentic AI translates into organisational learning outcomes.

3. Methodology

3.1 Research Design

An exploratory qualitative case study design was adopted, following Yin's (2018) framework for investigating complex contemporary phenomena within their real-life context. Agentic AI in higher education is sufficiently novel that the questions worth asking are still being formulated, and survey instruments with pre-specified variables would have imposed premature closure. A case study allows the institution to surface what matters while maintaining enough structure to generate transferable insights. The European University of Armenia was selected because it is actively engaged in AI integration under conditions of resource constraint and rapidly evolving national research policy, circumstances that are both distinctive and theoretically generative.

3.2 Participants

Twelve participants were selected through purposive sampling to represent the functions most directly implicated in agentic AI adoption: three senior academic leaders (Vice-Rector, Dean, and Research Director), four research office and research intelligence staff, three IT and digital strategy specialists, and two academic staff with research coordination responsibilities. Professional experience ranged from five to twenty years, and

all were directly engaged in KM, research analytics, or AI initiatives. Informed consent was obtained, and participation was voluntary throughout.

3.3 Data Collection

Data were collected through two complementary sources. Semi-structured interviews formed the primary instrument, developed from the literature on KM, research intelligence, learning organisations, and agentic AI. Questions explored current practices, the perceived capabilities and limitations of AI tools, governance and ethical concerns, and organisational readiness for deeper integration. Interviews ran over two months, each lasting 45 to 75 minutes, held in person or through secure online platforms, audio-recorded with consent, and transcribed verbatim. Institutional documents, including strategy reports, digital transformation policies, performance records, and KM guidelines, were analysed concurrently to triangulate findings and situate individual perceptions within the institution's formal strategy.

3.4 Data Analysis and Trustworthiness

Thematic analysis followed the six-stage process of Braun and Clarke (2006): familiarisation; initial code generation; theme identification; review and refinement; definition and naming; and interpretive write-up against the theoretical framework. To enhance transparency, the coding was organised into a data structure in the manner of Gioia, Corley and Hamilton (2013), in which first-order, informant-centred codes are progressively distilled into second-order themes and, finally, aggregate dimensions (Table 1). Coding was performed manually to sustain close engagement with participants' accounts. The resulting aggregate dimensions, namely agentic AI capabilities, research intelligence enhancement, strategic foresight mechanisms, organisational learning dynamics, and governance and ethical concerns, each correspond to one of the five propositions. Credibility was strengthened through data triangulation, member checking, and transparent documentation of analytical decisions. Reflexivity was maintained throughout, with the researchers' affiliations and prior dispositions toward AI monitored as potential sources of bias.

Table 1: Data structure (Gioia format)

First-order codes (informant terms)	Second-order themes	Aggregate dimension
"continuously updates insights without manual input"	Proactive, real-time sensing	Agentic AI capabilities
"integrate information from different units that were previously disconnected"	Integration of siloed data streams	Research intelligence enhancement
"anticipate future research priorities rather than just reacting"	Forward-looking strategic deliberation	Strategic foresight mechanisms
"staff may accept AI outputs without critical reflection"	Risk to reflective dialogue	Organisational learning dynamics
"transparency is essential; otherwise it is difficult to trust the system"	Trust contingent on transparency	Governance and ethical concerns

4. Results

Five thematic domains emerged, each matching one proposition. The findings are broadly affirmative but usefully complicated: the benefits are real, the conditioning factors demanding, and the risk to reflective dialogue serious. Representative verbatim quotations from the interview transcripts are reported below to tie the empirical data to the interpretive themes.

4.1 P1: Agentic AI Enhances Research Intelligence

Without exception, participants reported meaningful improvements in research intelligence after agentic AI integration. The intelligence available to decision-makers shifted from retrospective summaries to forward-looking signals (see Table 2). Several participants described the change as proactive; as one IT specialist put it, "the system brings relevant insights to us before we even think to ask."

Table 2: Agentic AI Contributions to Research Intelligence

Thematic Category	Evidence from Interviews	Observed Impact
Data Integration	"it connects funding, publications, and rankings in a way we couldn't do manually"	Reduced fragmentation across research functions
Predictive Analytics	"we're no longer just tracking performance—the system shows where things are heading"	Improved strategic positioning
Automated Monitoring	"it continuously updates what matters without needing someone to check"	Faster, better informed decision cycles
Scenario Modelling	"you can explore different scenarios and see potential outcomes instantly"	Enhanced capacity for anticipatory planning

Proposition P1 is strongly affirmed: agentic AI moved research intelligence from a reporting function to a sensing one.

4.2 P2: Research Intelligence Supports Strategic Foresight

The intelligence generated through agentic AI did not remain confined to research offices. Participants described a shift in leadership-level discussions: where meetings had previously centred on retrospective performance data, they increasingly incorporated AI-generated trend analyses, scenario projections, and opportunity maps. One senior leader put it: "AI helps us anticipate future research priorities rather than just reacting." Decisions about grant targeting, international partnerships, and faculty investment were reoriented around forward-looking intelligence rather than historical benchmarks (Table 3).

Table 3: Research Intelligence and Strategic Foresight Linkages

Strategic Area	Representative participant voice	Decision Outcome
Research Funding	"the system highlights funding directions, but we decide which ones fit our strengths"	More targeted, better timed proposal development
Internationalisation	"it shows emerging collaboration hotspots, but partnerships still depend on relationships"	Strategically aligned international partnerships
Faculty Development	"the system flags talent gaps, but we decide how to build those capabilities"	Focused mentoring and capacity-building initiatives

Proposition P2 is affirmed: AI-derived research intelligence reoriented leadership deliberation toward forward-looking decisions.

4.3 P3: Agentic AI Strengthens Knowledge Creation and Sharing

The picture here is more nuanced. On the positive side, AI-enabled dashboards and automated reporting reduced information silos: as one participant noted, "we now integrate information from different units that were previously disconnected." A recurring concern also emerged: that the fluency of AI-generated summaries might displace the slower, more friction-laden processes of collegial debate through which collective understanding develops. As one research coordinator cautioned, "there is a concern that staff may accept AI outputs without critical reflection." This concern was not unanimous; a minority regarded it as overstated, arguing that automating routine summarisation frees time for deeper debate rather than eroding it (Table 4).

Table 4: Impact on Knowledge Creation and Sharing Processes

KM Dimension	Observed Change	Participant Perception
Knowledge Accessibility	Marked increase in cross-institutional transparency	Positive

KM Dimension	Observed Change	Participant Perception
Cross-Departmental Sharing	Improved visibility of research activities and outputs	Positive
Reflective Dialogue	Risk of automated outputs replacing deliberative discussion	Mixed; concern expressed across seniority levels, though contested by a minority
Knowledge Codification	Automated summarisation of research activity	Efficient, but requiring active human oversight

Proposition P3 is partially affirmed: the accessibility gains are genuine, but so is the risk to reflective dialogue, which participant views leave unsettled.

4.4 P4: Research Intelligence as the Interpretive Intermediary

A consistent pattern was the indirectness of agentic AI's contribution to strategic foresight. Participants did not describe AI as producing decisions, but as producing intelligence that informed human deliberation. One research director put it: "AI acts almost like a research assistant, not just a tool." Remove the human capacity to interpret and translate AI outputs into institutional terms, and the chain breaks. Participants described a sequence, not a direct effect: agentic AI produced intelligence that humans interpreted into foresight. Proposition P4 is affirmed: institutions that deploy agentic AI without investing in the human capacity to use it are likely to be disappointed.

4.5 P5: Governance and Human–AI Collaboration Condition AI Impact

Trust recurred most persistently in discussions of AI governance. Participants acted on AI-generated recommendations only when they understood the basis for them and were confident that safeguards existed against bias and error. One participant summarised the condition: "transparency is essential; otherwise, it is difficult to trust the system." Where governance frameworks were clear and accountability mechanisms visible, AI outputs were engaged with as credible inputs; where they were absent, participants reverted to traditional decision-making, rendering the AI investment redundant (Table 5).

Table 5: Conditioning Factors in AI-Enabled Knowledge Management

Conditioning Factor	Representative participant voice
Data Governance Framework	"you need clear rules on when to trust the system and when to challenge it"
Human Oversight	"human oversight is essential—we can't delegate judgement to the system"
Ethical Guidelines	"there's always a question of whether we're seeing the full picture or a filtered one"
Digital Literacy	"if we don't understand how it works, we're cautious about using it"

Proposition P5 is affirmed: governance and human–AI collaboration are not soft considerations but the structural conditions on which the entire value proposition of agentic AI depends.

4.6 Summary of Proposition Assessment

Table 6: Summary of Proposition Assessment

Proposition	Summary	Assessment
P1	Agentic AI shifts research intelligence from retrospective to anticipatory	Strongly affirmed
P2	Research intelligence bridges AI capability and strategic foresight	Affirmed

Proposition	Summary	Assessment
P3	AI improves knowledge access but risks displacing reflective dialogue	Partially affirmed
P4	Research intelligence mediates AI's foresight contribution	Affirmed
P5	Governance and human collaboration condition AI's strategic value	Affirmed

5. Discussion

The findings invite a recalibration of how universities think about AI investment. Higher education leadership has tended to frame AI either as an efficiency tool or as an existential threat to academic values; neither frame captures what this study describes. Agentic AI, when properly deployed and governed, is an institutional sensing capability that extends the organisation's ability to notice what it would otherwise miss and amplifies human strategic reasoning without substituting for it.

5.1 Agentic AI and Research Intelligence: Beyond Efficiency

The strong support for P1 adds empirical texture to a largely theoretical argument. Davenport and Ronanki's (2018) case for AI rests primarily on efficiency gains; this study suggests, in line with Alavi, Leidner and Mousavi's (2024) reframing, that agentic AI's more consequential contribution is epistemological rather than operational. By integrating previously siloed data streams into a continuously updated intelligence picture, it enables the environmental sensing that Teece (2007) identifies as the first component of dynamic capability.

5.2 The Mediation Insight: Why the Intelligence Layer Matters

The mediation finding is arguably the study's most practically significant contribution. Institutions that implement agentic AI without developing their human research intelligence capacity make a category error: the AI generates signals, but without trained interpreters who understand institutional context and disciplinary nuance, those signals do not become intelligence and cannot support foresight. McAfee and Brynjolfsson (2017) note that the organisations benefiting most from AI redesign their workflows around it rather than bolting it on; in higher education, this means investing in professionals who engage with AI outputs critically rather than deferentially.

5.3 The Dialogue Risk and the Limits of Confirmation

The partial support for P3 carries a warning that deserves more than a footnote. The concern that fluent, authoritative-seeming AI summaries might displace the deliberative processes through which academic communities develop shared understanding resonates with Senge's (1990) argument that organisational learning is irreducibly social, and with Alavi, Leidner and Mousavi's (2024) caution that generative systems may erode the social validation of knowledge. Knowledge is not merely information; it is information that has been tested, contested, and provisionally agreed upon through dialogue. An AI system can summarise what is known; it cannot replicate the process through which a community decides what matters and why.

It is equally important to resist reading the data as straightforward confirmation of the framework. First, the dissenting minority on P3 may be correct: automating routine summarisation could liberate time for the very debates critics fear will atrophy, an interpretation the present data cannot adjudicate. Second, participants' overwhelmingly positive accounts may partly reflect enthusiasm and social desirability; respondents involved in AI initiatives have an interest in their success, and the absence of disconfirming voices is itself a finding to treat with caution rather than as corroboration. None of the reported foresight outcomes were independently benchmarked against decision quality, leaving open the possibility that the perceived gains are, in part, narrative rather than substantive.

5.4 Governance as the Enabling Condition

The support for P5 reframes governance from a compliance burden to a strategic enabler. Participants engaged critically with AI outputs because governance frameworks gave them confidence that the outputs were trustworthy and accountability structures clear. This aligns with Leonardi's (2011) socio-technical perspective: technology's organisational effects are never properties of the technology alone but of the human–technological

assemblage in which it operates. The investment in governance is part of the investment in AI, not separable from it.

5.5 Theoretical Contributions

This study makes three connected contributions to KM theory. First, it provides empirical grounding for AI as an augmentative intelligence layer, a term that captures agentic AI's role more precisely than either "tool" or "actor". Second, it synthesises KM theory, learning organisation theory, dynamic capabilities, and research intelligence scholarship into an integrated framework for AI-enabled foresight. Third, it contributes context-specific evidence from an emerging university in Armenia, whose distinctive constraints generate insights that large, well-resourced Western institutions cannot.

5.6 Limitations

The study's contribution should be weighed against its design limitations. As a single-case study, it prioritises depth over breadth; its findings are analytically generalisable to theory (Yin 2018) rather than statistically generalisable to a population, and the specific organisational, national, and resource conditions of the European University of Armenia may not transfer elsewhere. The sample of twelve, while appropriate for exploratory qualitative work, is small and was drawn exclusively from individuals already engaged in AI initiatives, introducing a probable selection bias toward favourable views. Reliance on self-reported perceptions, gathered at a single point in time, cannot establish whether the reported gains translated into measurable institutional outcomes or whether they persist. Finally, the researchers' institutional affiliation, although reflexively monitored, remains a potential source of bias. These constraints temper the claims and frame the agenda for future work.

6. Conclusion

Universities were built to manage knowledge, yet many manage it badly: hoarding what they know, losing what they have learned, and arriving late to futures they should have anticipated. Agentic AI does not resolve this automatically, but under the right conditions it alters what is possible.

This study suggests that agentic AI can reorient a university's relationship with its own knowledge, shifting it from custodianship to active intelligence generation and from retrospective accounting to anticipatory sensing. At the European University of Armenia, AI integration was associated with perceived improvements in research intelligence that appeared to propagate into strategic decision-making. The pathway was not direct: research intelligence, interpreted by human decision-makers within robust governance frameworks, was the indispensable mediator.

The practical messages follow directly. Leaders should not invest in agentic AI without equal investment in the human and governance infrastructure that makes its outputs actionable; knowledge managers should reposition research intelligence from a reporting backroom to a strategic frontline; and policy-makers should develop ethical and accountability frameworks before deployment rather than after. Future research employing multi-institutional, mixed-methods, and longitudinal designs, with attention to the dialogue risk in P3 and to independent benchmarking of foresight outcomes, would deepen the evidence base. Agentic AI offers universities not a shortcut to strategic wisdom but a better starting point for the human deliberation that produces it.

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research design, data collection, empirical analysis, interpretation of findings, and theoretical arguments, were carried out by the authors. All AI-assisted content was critically reviewed, substantially revised, and verified against primary sources by the authors prior to submission.

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