AGENTIC AI – THE TRANSFORMATION OF DECISION-MAKING PROCESSES THROUGH ARTIFICAL INTELLIGENCE

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Abstract

Agentic AI describes a new generation of AI that automates tasks, pursues goals independently, makes decisions and proactively interacts with its environment. This study - based on a qualitative exploratory research design with expert interviews - aims at understanding how the use of such systems affects internal decision-making logic and organizational structures in companies. Results show that Agentic AI changes decision-making processes. Decisions are being made by systems and humans, with humans mainly taking on supervisory or control functions. We provide a theoretical contribution to existing decision-making and organizational theories with practical recommendations for dealing with such autonomous AI systems.

Introduction

Traditional decision-making processes are reaching their limits due to the availability of large amounts of data, the increasing speed at which market changes occur, and the need to remain competitive in the global marketplace. The dynamic development of AI has the potential to fundamentally change the way companies operate in different industries (IT-P, 2024). In Architecture, Engineering and Construction (AEC), AI adoption is still very limited as reported in the global RICS survey (2025).

AI systems are often used in content generation, data analysis, and forecasting. However, research shows that increasingly powerful autonomous systems, e.g. Agentic AI (Stryker, 2024) are finding its way into practice. This technology goes beyond traditional AI systems in that it is capable of solving complex, multi-stage problems that have no fixed rules or predefined solutions. Agentic AI thus represents an advanced form of AI that can assume a supportive role, as well as act independently. This offers companies the opportunity to optimize decision-making processes and increase efficiency. The Harvard Business Review describes how these systems are transforming human-machine collaboration through their capabilities, for example in virtual nursing or AI-supported travel planning (Purdy, 2024), managing smart homes (Sepkota et al., 2026) or assisting in Urban Planning (Finn & Downie, 2025). Companies like PricewaterhouseCoopers (2024) emphasize the transformative influence of multimodal frameworks in which specialized AI agents work together to optimize efficiency and decision-making processes on an unprecedented scale. At the same time, research by Berkeley SCET highlights the opportunities and risks of these systems, in particular their adaptability to changing conditions and their ability to achieve specific goals autonomously (Ghose, 2024). Simultaneously, key questions arise regarding the area of application and the comprehensive effects, particularly with regard to transparency, accountability, and the delegation of decision-making powers to AI within the internal organization (Ghose, 2024; Purdy, 2024; Stryker, 2024).

In this context, it is becoming increasingly important to examine the organizational and strategic implications of Agentic AI. It is necessary to clarify in which business areas this technology can be used effectively, how it should be introduced, and what capabilities are required for its implementation. This raises the following research question: *"How is Agentic AI integrated into organizational systems to optimize decision-making processes, and what impact does this integration have on the internal structure?"* Hence, this scientific paper examines the effects of Agentic AI on decision-making processes and organizational structures in companies.

First, we examine the status-quo on Agentic AI and decision-making processes. Second, we conduct a qualitative study to explore the experts´ perspectives on AI integration and its implementation effects in organizational settings. This is followed by an analysis and discussion of the interview results, as well as theoretical and practical implications. Finally, we conclude with limitations of the study and related starting points for possible further research in this area.

Theoretical foundation

Decision-making processes in organizations

Research on organizational decision-making has evolved from idealized rational models to more realistic approaches that account for human and structural limitations. The classical rational model, grounded in the *homo economicus* assumption, posits fully informed decision-makers who maximize utility (Suchanek, 2021).

In practice, however, constraints such as incomplete information, time pressure, and bounded cognitive capacity prevail. Simon (1955) addressed these realities with the concept of bounded rationality, according to which decision-makers seek satisfactory rather than optimal solutions. Complementary models highlight the roles of intuition, incrementalism, and uncertainty (Lindblom, 1959; Dane & Pratt, 2007; Cohen et al., 1972; Kahneman & Tversky, 1979).

Decision-making also varies by planning horizon. Operational decisions address short-term, routine matters, tactical decisions focus on medium-term resource allocation, and strategic decisions shape long-term organizational direction. Complexity and uncertainty increase with the decision level, influencing information needs and responsibility distribution (Chopra & Meindl, 2007; Misni & Lee, 2017).

Organizational structure and culture further shape decision processes. Bottom-up approaches, common in agile settings, emphasize decentralized and participatory decision-making, while top-down hierarchies concentrate authority. Group-based decisions, such as those in interdisciplinary AEC project teams, benefit from diverse perspectives but risk groupthink (Turner & Pratkanis, 1998).

This variety raises a central question: how should decision-making rights (DR) be distributed — centrally or decentrally? In modern organizations, DR are increasingly differentiated. Specific rights apply to codifiable processes, whereas residual rights remain in complex, uncertain situations. Sreckovic and Windsperger (2023) demonstrate, using blockchain-based organizations, that the degree of centralization depends largely on the codifiability of knowledge. The more a process can be formalized, the greater the potential for automation. Although derived from blockchain, this framework provides a valuable analogy for analyzing the impact of Agentic AI on organizational decision-making.

Limits of classic decision-making models

Modern decision-making faces increasing complexity, rapid market changes, and vast data volumes, exposing the limitations of traditional models (Davenport & Harris, 2007). Decisions are frequently made under conditions of incomplete information, time pressure, and cognitive constraints, which foster biases such as confirmation and overconfidence, as well as emotional misjudgments. Structural barriers—including information silos, lack of real-time data, and limited scalability—further restrict human decision-making capacity, particularly in dynamic environments (Berthet, 2021).

These constraints explain the growing importance of technology-based support systems. While business intelligence (BI) enables data-driven insights and real-time decision support (SAP, n.d.-b), Agentic AI goes further by independently analyzing situations, making decisions, adapting to change, and acting proactively (Stryker, 2024).

AI Agents and Agentic AI

Agentic AI is a key technology for automating complex tasks and enabling autonomous decision-making in dynamic, unpredictable environments (Finn & Downie, 2025). Unlike traditional AI systems that act reactively,

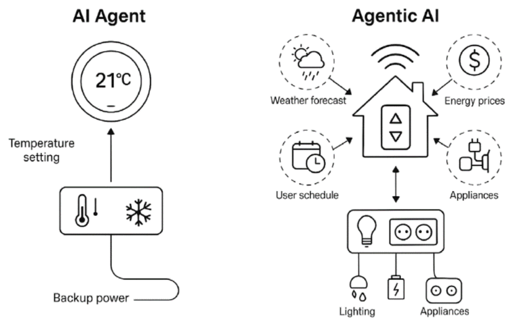

Figure 1: Comparative illustration of AI Agent vs. Agentic AI (Sapkota et al., 2026, p. 8)

agentic systems operate independently: they recognize goals, plan multi-step tasks, and orchestrate external tools or sub-agents to achieve outcomes (Stryker, 2024; Weiler. 2024). By combining the linguistic versatility of large language models with the structured precision of traditional programming, Agentic AI enables end-to-end automation of complex processes (Guan et al., 2024; Stryker, 2024; Finn & Downie, 2025). Rather than generating content on demand, these systems act proactively as goal-oriented collaborators, as illustrated in the smart home example (Figure 1).

The integration of Agentic AI into business processes shifts decision-making from passive suggestions to active, autonomous execution (Ismail, 2025; Fincken, 2024). While generative AI focuses on linguistic content, agentic systems introduce a new automation logic through strong reasoning, modular tool use, and goal pursuit, expanding their applicability across industries (Deslandes, 2025; Zhang, 2025). Key distinctions between AI paradigms are summarized in Table 1 (Sapkota et al., 2026).

Table 1: Key Differentiating Attributes of AI Agents, Agentic AI, and Generative Agents

Aspect	AI Agent	Agentic AI	Generative Agent
Primary Capability	Task execution	Autonomous goal setting	Content generation
Planning Horizon	Single-step	Multi-step	N/A (content only)
Learning Mechanism	Rule-based or supervised	Reinforcement/meta-learning	Large-scale pretraining
Interaction Style	Reactive	Proactive	Creative
Evaluation Focus	Accuracy, latency	Engagement adaptability	Coherence, diversity

AI in AEC

The literature in the AEC domain shows that AI implementation is primarily focused on automated design generation, building performance optimization, system diagnostics enhancement, digital twin operations, and assistance in urban-scale planning, with the broader context of the built environment missing such as the building life-cycle (Lee et al., 2025; Khodabandelu &

Park, 2021; Piccialli et al., 2025). In their review of currently existing AI deployment limitations, Lee et al. (2025) mention: 1) predominant reliance on user-side prompt engineering (lack of a structured knowledge engineering framework); 2) missing comprehensive AI workflows and no knowledge integration with existing systems; 3) deficiencies in standardization and real-world validation (absence of in-depth real-world application resp. evaluations for benchmarking). Regarding collaborative integration and decision-making, Lee et al. (2025) argue that Agentic AI can enhance existing workflows and accelerate the transition toward Human-AI collaboration in the built environment.

The question remains here – how would these scalable integrations of AI work in the organizational setting and decision-making context? So far on the global level, the construction sector shows significant barriers to adopting and scaling AI use, including lack of skilled personnel; integration with existing systems – where companies strive to find flexible and transparent integration options from technology vendors, i.e. interoperable systems for AI integration with their current existing solutions, organizational structures and workflows; data quality and availability; and high implementation costs (RICS, 2025).

Methodology

Study design and sample

Agentic AI represents a novel and under-researched field, particularly regarding its organizational integration and implications. Given the absence of consolidated theoretical frameworks, a qualitative exploratory research design was adopted to generate new insights rather than test existing hypotheses (Corbin & Strauss, 2008).

Semi-structured expert interviews were selected as the data collection method, as they are well-suited for exploring complex, dynamic, and emerging topics and provide access to specialized expert knowledge (Patton, 2002; Saldaña, 2013). The interview guide was divided into five thematic blocks: (1) professional background of the interviewees and their points of contact with Agentic AI, (2) areas of application and potential of Agentic AI, (3) integration into internal company decision-making processes, (4) organizational and procedural implications, and (5) future prospects and integration recommendations. The guide was slightly adapted during the course of the survey in order to specifically address and further develop findings from previous interviews, such as the distinction between Agentic AI and Generative AI (Urquhart et al., 2010).

The interviewees were selected through criterion sampling, focusing exclusively on experts with direct experience in agent-based AI systems. The final sample comprised seven experts from the SAP corporate ecosystem, including SAP in-house specialists, implementation partners, and customer-side users already deploying Agentic AI productively. This diversity of roles — spanning technical, strategic, and innovation perspectives — enabled a multifaceted understanding of both technological and organizational aspects of Agentic AI integration. The focus on the SAP environment was deliberate, given the company's leading position in enterprise software and its substantial strategic investment in Agentic AI (Katanich, 2025; SAP, 2025). The ecosystem provides rich insights that are expected to be transferable to the AEC industry.

Data collection and analysis

The seven semi-structured interviews were conducted in German and English from June to July 2025, based on an interview guide that included open-ended questions.

The interview data was evaluated using the qualitative analysis software ATLAS.ti as part of a combined deductive-inductive process. The coding in ATLAS.ti yielded some insightful and interesting findings regarding the integration and impact of Agentic AI in decision-making processes. Table 2 shows a coding example.

Key topics were derived from the literature, systematically queried, and the corresponding responses were coded deductively. This was supplemented by an inductive approach, in which new categories and patterns, developed from the material, were identified and coded in summary form (Gioia et al., 2012, p. 10; Mayring & Fenzl, 2019, p. 641; Saldaña, 2013, p. 9).

Generated from ATLAS.ti, Table 3 provides an overview of all categories, including the corresponding number of codes, the assigned code group based on the structure of the interview guide, and the number of associated quotes. A total of 74 codes were applied to 325 quotes from seven

Table 2: Exemplary coding

Code group	Category	Code	Quote
Applications & Potential of Agentic AI	Current Applications	Variety of Agents	*"And we already have an agent in use, so to speak—this Classification Agent—which is currently helping in our call centers to structure customer inquiries. It essentially identifies the correct category for the inquiry so that the right agent can then work on the ticket. That was a big step forward. "* (Interviewee No. 2) *"It looks at your code, makes suggestions, writes code for you—whatever you want. Cursor is probably the agent I use the most. It basically executes code for you, writes code for you, tests the code for you, pushes it to GitHub into this external environment where you share the code with others, and also performs the operations you want there."* (Interviewee No. 7)
Effects of Integration	Structural Changes	Regulated Decision-Making & Decision Support	*"[Fully autonomous decision-making] will probably come eventually, but I don't see it happening right now; though I actually think it's quite good."* (No. 1) *"Yes and no—regulated decision-making, that is. It's not simply the system deciding a large part of our business plan, for example. It's about specific and limited decisions for specific environments."*(No. 7)

Table 3: Coding overview

Category	Nr. of Codes	Group / Document Group	Nr. of Quotations
Agentic AI Characteristics	3	Context & Definition	16
Prerequisites for Use	6	Agentic AI Integration in Decision-Making Processes	40
Action Recommendations	5	Outlook & Recommendations	57
Long-term Effects	5	Outlook & Recommendations	46
Codifiability of Processes	7	Agentic AI Integration in Decision-Making Processes	15
Potential Areas of Application	5	Areas of Application and Potentials of Agentic AI	17
Current Areas of Application	8	Areas of Application and Potentials of Agentic AI	54
Critical Areas of Application	5	Areas of Application and Potentials of Agentic AI	15
Structural Changes	7	Effects of Integration	63
Processual Changes	9	Effects of Integration	64
Risks	9	Agentic AI Integration in Decision-Making Processes	25
Opportunities	5	Agentic AI Integration in Decision-Making Processes	12

interviews. Some quotes were assigned to multiple codes, as they address various aspects simultaneously. The coding was carried out in several cycles according to Saldaña (2013). In the first cycle, in-vivo coding (recording of direct quotes) and structured coding (thematic categorization based on the interview guide) were combined to capture both the interviewees' verbatim statements and the key thematic areas. Deductive coding was applied to, among others, "Agentic AI characteristics: Autonomous," "Structural changes: Centralization," or "Codifiability of processes," as these were specifically addressed in the interview guide. Additionally, categories with codes were developed inductively from the empirical material—for example, "Prerequisites for deployment: Cost-effectiveness over hype," "Structural Changes: Agents as Team Members," or "Long-Term Effects: Changed Work Methods & New Competency Requirements." In the second cycle, thematically related codes were bundled, abstracted, and merged into higher-level codes using *pattern coding*. This thematic grouping reduced the complexity of the analysis without losing depth of content. To avoid excessive differentiation through individual codes and the resulting high complexity of the analysis given an exceptionally large number of codes, thematically related codes were consolidated. For example, statements that were originally coded separately, such as "Test locally, then scaled centrally," "Test user groups," "Iterative approach," and "Trial & Error," were grouped into a single subcategory: "Test phase & scaling".

Discussion of results

This study provides answers to the research question of *how Agentic AI is integrated into corporate systems to optimize decision-making processes and what effects this integration has on the internal structure*.

The interview results show that Agentic AI is currently being implemented primarily as intelligent assistance that supports, accelerates, and partially automates decision-making processes—but without completely delegating control. Integration is taking place gradually and selectively, depending on the technological and organizational maturity of the company.

A common thread runs through the interviews: there is agreement on many aspects – in particular on the supporting role of Agentic AI, the importance of technical prerequisites such as data quality and system transparency, and the need for human control in the sense of a human-in-the-loop principle. At the same time, differing perspectives and uncertainties arise on key issues such as the codifiability of processes: some respondents consider it an indispensable prerequisite for the use of agents, while others see modern LLM-based architectures as sufficiently flexible to automate even semi-structured processes. The integration of Agentic AI is already having structural effects. New roles have been identified, such as agent architects and strategic AI managers, who do not perform operational tasks but instead coordinate the technology in a targeted manner. At the same time, Agentic AI is transforming traditional decision-making processes and contributing to the reorganization of workflows, for example, by automating repetitive tasks. Simultaneously, there is an apparent discrepancy between the way it is presented in publications and its actual implementation in practice.

All interviewees recognize the potential of Agentic AI, particularly with regard to efficiency gains, process improvements, and new forms of decision support. The central challenge is how and under what conditions it can be sustainably integrated into existing structures.

Organizational prerequisites and design factors

The successful integration of Agentic AI into corporate decision-making processes is not solely a question of technological feasibility- it strongly depends on organizational and infrastructural prerequisites. Many of those are not only conditions for meaningful use, but offer concrete recommendations for action for successful and sustainable implementation. They are therefore consolidated in Table 4 as key success factors. To enhance practical utility, we augment each factor with concrete implementation examples drawn from the expert interviews and measurable success metrics.

Current market studies also illustrate that the use of Agentic AI often fails due to a lack of system transparency, fragmented IT landscapes, and inadequate infrastructure. Belcic and Stryker (2025) and Sj (2025)

Table 4 : Key Success Factors with Metrics

Success Factor	Description	Implementation Example (from interviews / practice)	Suggested Success Metrics
Economic efficiency over hype & Strategic selection	Focus on business value rather than technology trends; prioritize use cases	One SAP partner expert described starting with a procurement classification agent that flags non-compliant invoices before full automation (reducing manual review by ~40% in pilot). Similar to Coupa's autonomous procurement intelligence	ROI of agentic initiatives; cost savings vs. implementation effort; prioritized use-case coverage rate
System transparency & process clarity	Clear system landscape SAP workflows first and integrable, data-supported workflows	Interviewees emphasized mapping existing SAP workflows first (e.g., end-to-end procure-to-pay) beforeintroducing agents. DHL-style real-time logistics agents require interoperable date pipelines	Process mapping completeness score; quality index; system integration error rate
Technological & organizational implementation capabilities	Digital infrastructure foundation plus internal resources	Experts recommended pilot projects in logistics/supply chain using SAP Joule as a digital assistant before scaling to multi-agent orchestration	Infrastructure readiness score; training hours per employee; internal AI skill coverage
Governance & agent logic	Defined responsibilities, control structures, and comprehensible agent objectives	SAP customer-side expert described a multi-level approval workflow; agents handel routine procurement decisions up to €50k threshold, with automatic escalation to human "AI managers" above that	Agent goal alignment score; transparency/explainability index; governance policy adherence rate
Human control & monitoring	Human-in-the-loop structures with continuous oversight	All interviewees stresses "supervisory" roles; one example involved a quality-control agent in manufacturing that requests human input on edge cases (e.g., unusual material defects)	Human override rate (<15% target for codifiable processes); escalation frequency trend
Responsibility & Supervision /Change management & test phase	Iterative introduction with pilot phases and stakeholder participation	Experts advocated starting with 3-6 months pilots (e.g., ticket classification or invoice agent) followed by feedback loops and role definition workshops	Adoption rate; employee trust/satisfaction score (via pulse surveys); pilot-to-scale success rate

emphasize the need for robust, scalable architectures, while Noureen (2025) points out that despite a projected potential of over USD 450 billion, many companies do not have the technological maturity and organizational capability to implement it. These findings are consistent with the interviews conducted for this study, in which statements regarding the success factors "system transparency & process clarity" and "technological & organizational feasibility" was mentioned repeatedly. In addition, Shavit et al. (2023) provide concrete governance practices for the responsible use of Agentic AI. They emphasize the importance of transparent agent logic, automated monitoring, and limiting scope for action, thereby underscoring the relevance of the empirically derived factors "governance & agent logic" and "human control & monitoring".

Table 5 shows examples of areas of application and associated agent solutions that have already been discussed theoretically in this paper and have now been empirically confirmed (Capgemini, 2025; Dudley & DelMastro, 2025; Finn & Downie; Weiler, 2024).

Organizational transformation and decision-making rights

Agentic AI is currently understood primarily as a support system that structures, accelerates, and supplements decision-making processes, but not as an autonomous decision-maker. The experts surveyed describe a hybrid control model in which humans increasingly act as "AI managers" (Nicoud, 2025; Raskovich et al., 2024).

Responsibility remains deliberately with humans, especially in sensitive or strategic contexts, in contrast to simple and predominantly operational decisions, which can be automated to a greater extent. This tension between automation and control is consistent with the literature on human-in-the-loop principles and the emphasis placed by Shavit et al. (2023).

Table 5: Exemplary areas of application

Administration	Granola Note-taker, follow-up emails after meetings
Logistics & Supply Chain	Quality control agent, invoicing agent
E-commerce	Shopping agent
Marketing, Sales & Service / CX Area	Ticket Classification Agent, User Story Refinement Agent
Travel Industry	Booking Agent
Support	Code Generation / Cursor Pro / GitHub, Web Application, Security Agent
Wide range of applications	Digital Assistant Joule, Test Automation Agent
AEC	Autonomous calculations, code compliance check; proactive BIM model validation, clash resolution suggestions; risk-monitoring etc.

To move from current supporting roles toward more advanced hybrid decision-making, organizations can follow this practical pathway (derived from interviewee forward-looking statements and aligned with emerging industry roadmaps):

1. ***Pilot Stage (Awareness & Selective Automation)***: Focus on narrow, high-volume, codifiable tasks (e.g., invoice classification, routine scheduling). Emphasize data quality, transparency, and human oversight. The goal: Prove value and build internal trust.
2. ***Scaled Integration Stage (Hybrid Orchestration)***: Expand to multi-step processes involving sub-agents

(e.g., procurement agent coordinating with logistics and compliance agents). Introduce new roles such as agent architects and AI governance leads. Governance frameworks become central.

3. ***Optimized Autonomy Stage (Strategic Human-AI Collaboration)***: Agents handle end-to-end operational decisions with minimal intervention in well-defined domains, while humans focus on strategic oversight, exception handling, and innovation. Continuous learning loops and ethical guardrails are fully embedded. This pathway helps companies progress gradually while mitigating risks such as loss of control or competence erosion.

The interviews also show that Agentic AI is increasingly seen as a team member rather than just a technical tool. Agents take on preparatory tasks, while final responsibility remains with humans—a division of roles that is also reflected in theory. At the same time, there is tension between decentralized use (in specialist areas) and centralized control through governance and monitoring (Accelirate, 2025; Nicoud, 2025). Efficiency and scalability can be ensured through central standards and control.

The codifiability framework also finds confirmation here. While standardized, codifiable decisions are increasingly being made automatically, residual decision-making rights in unclear, dynamic situations remain with human actors. In practice, therefore, Agentic AI is not used as a substitute, but as a cognitively complementary system (Sreckovic & Windsperger, 2023).

At the same time, organizational shifts are becoming apparent: new roles and skills are emerging, such as prompt designers, agent architects, and agent orchestrators; traditional process responsibilities are being replaced by cross-functional coordination and monitoring tasks. Successful integration of Agentic AI is not only a technical challenge, but an organizational transformation process – with clear responsibilities and new roles (Ismail, 2025; Nicoud, 2025).

Areas of tension and open questions

Despite the recognizable progress and potential associated with the use of Agentic AI, key areas of tension and unresolved issues remain. These relate not only to technological and organizational dimensions, but also to ethical, legal, and social aspects. A key area of tension is the discrepancy between public expectations and corporate reality. While media reports and specialist publications often outline the increasing dominance of autonomous, proactive agents, practical reports and the present study show that companies are currently still struggling with fundamental challenges: a lack of process standards, limited data quality, fragmented IT landscapes, and cultural reservations are hindering implementation (Belcic & Stryker, 2025; Dudley & DelMastro, 2025; Noureen, 2025). Another key area of tension concerns the relationship between autonomy and control. The more powerful Agentic AI becomes, the more pressing the question of legal, ethical, and operational frameworks becomes. Without clear accountability, comprehensible agent goals, and ethical guidelines, there is a risk of losing control—not only technically, but also socially (Weiler, 2024; Zhang, 2025). In addition, questions of efficiency versus competence development are gaining in importance. As agents increasingly take on routine tasks, junior roles in particular are coming under pressure. This is preventing learning and development opportunities, hence poses risk to the long-term retention of competence in organizations.

Furthermore, authors such as Ghose (2024) and Shavit et al. (2023), in line with the experts in this study, call for robust governance approaches not only at the corporate level, but also by social actors. In this context, governance refers to the entirety of institutional regulations, processes, and control mechanisms for the responsible design, control, and monitoring of technology use. This includes, e.g. legal minimum standards for transparency, data protection, the control of algorithmic biases, and the traceability of agentic decisions.

Finally, security risks should not be underestimated. Lack of traceability, potential for abuse, inadequate training, or hallucinations can have legal, technical, commercial, and social consequences. These risks, which were addressed in the interviews, are also confirmed in other articles (Ghose, 2024; Ramel, 2024).

New AEC Implications

Although the empirical findings are rooted in the SAP enterprise ecosystem, they carry relevant implications for the AEC industry, where AI adoption remains limited and fragmented (RICS, 2025; Lee et al., 2025). Construction projects are characterized by high uncertainty, fragmented workflows, data silos across design, procurement, and on-site execution, and stringent requirements for safety, compliance, and lifecycle performance. Agentic AI can address these challenges by enabling proactive, multi-step automation that goes beyond current reactive tools. For instance, agentic systems could autonomously validate BIM models in real time, detect and resolve clashes, monitor project risks through integration with digital twins and sensor data, and optimize resource allocation across supply chains while escalating complex or high-stakes decisions to human supervisors.

Drawing on the success factors, AEC organizations could begin with targeted pilots in codifiable areas such as automated code compliance checks or progress reporting, then progress toward hybrid orchestration involving coordinated agents for design optioneering, predictive scheduling, and sustainability assessments. The human-in-the-loop governance structures and phased transition pathway proposed here are particularly valuable in construction's risk-averse environment, where full autonomy must be balanced with accountability and regulatory compliance. As noted by Lee et al. (2025),

Agentic AI has strong potential to accelerate the shift toward true Human-AI collaboration in the built environment, yet success will depend on overcoming barriers such as poor data interoperability, skills gaps, and fragmented IT landscapes—precisely the organizational prerequisites emphasized in our findings. Future AEC-specific applications could therefore benefit from adapting the codifiability framework and governance logic to the sector's unique project-based and multi-stakeholder context.

Limitations and further research

The results are based on a limited number of expert interviews with seven participants from the SAP corporate environment. This provided focused insight into the current practice and perception of Agentic AI, but limits the representativeness and generalizability of the results. In addition, all interview partners come from the Austrian/Germany/Switzerland region, which results in geographical homogeneity and limits the application to other cultural or economic contexts. Furthermore, the study is a snapshot of a dynamically developing field of research. Agentic AI is still in the pilot stage in many organizations, which is why numerous assessments are based on hypothetical assumptions or early experience. Rapid technological development can mean that individual findings become obsolete in a short period of time. Conceptual limitations are also apparent at the theoretical level. The analysis is primarily based on decision-making and organizational theory as well as the concept of codifiability. Other theoretical perspectives, such as ethical or legal approaches, were not systematically included. While this deliberate focus enables a targeted analysis of organizational decision-making processes, it also opens up space for future interdisciplinary research.

Despite methodological rigor, a certain degree of subjective interpretation is unavoidable when evaluating qualitative data. The subjectivity of the statements and potential distortions pose further methodological challenges. Future studies should specifically address these limitations. Quantitative studies with larger and more diverse samples could help to validate the patterns identified in this study and test their transferability to other contexts. There is also a need for further research in the form of longitudinal studies that examine changes in decision-making structures, role profiles, and governance systems over a longer period of time.

Conclusion

In the long term, the use of agentic AI will not only bring technological innovations, but also profound changes for organizations. This is not just a matter of more efficient processes, but of structural change. Working methods are changing, new roles are emerging, and the requirements for skills are shifting significantly—especially in the coordination and responsible control of intelligent agents. At the same time, the tension between technological progress, regulatory frameworks, and sustainable action remains. While autonomous agents appear as key decision-makers in some future scenarios, the question remains as to how much responsibility such systems can—and should—actually assume. The increasing pressure to innovate and rapid developments in the field of AI require companies not only to invest in technology, but also to develop a new understanding of leadership, trust, and responsibility, as well es AI Capabilities. These areas of tension mark central topics for future research and the governance of Agentic AI design.

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