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Could it be more than a toolbox? Defining a business model for artificial intelligence-driven general contractors

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Abstract

Purpose – The purpose of this research is to address the potential of artificial intelligence (AI) to drive business models for general contractors. While AI is used for various tasks, its holistic impact on general contractors' business models remains unclear.

Design/methodology/approach – The research utilizes a qualitative, multi-stage, action-research-oriented study. The methodology includes a literature review, two internal company workshops to design a specific business model and a third validation workshop with 25 industry experts to broaden and generalize the model.

Findings – The research provides a transferable, AI-driven business model structured around Osterwalder's business model canvas components. It details a gradual adoption pathway for general contractors, addressing the tension between AI as an operational tool and as a transformative force. The pathway starts with internal efficiency enhancements (an incremental "toolbox" approach), progressing to value-added client services and culminating in transformative, servitized offerings such as project-independent AI-as-a-Service (AIaaS).

Originality/value – This study addresses a significant gap – AI-driven business models for general contractors are largely missing from the existing research. It moves beyond viewing AI as a toolbox for isolated tasks to explore its potential to reconfigure the entire business system. The research provides a timely and structured overview that is valuable to both industry and academic actors by conceptualizing the AI-driven contractor as a data-driven ecosystem orchestrator.

Keywords Artificial intelligence, Business model, General contractor, Construction industry, AI-as-a-service, Digital transformation, Servitization

Paper type Research article

1. Introduction

The construction industry has been characterized by stagnant productivity, fragmentation and pressing sustainability concerns (Ahmad *et al.*, 2020; European Commission, 2023; UNEP, 2023; Mischke *et al.*, 2024). Compared against this landscape, AI has trended as a technology with the claimed potential to address industry problems (Abiouye *et al.*, 2021; Forcael *et al.*, 2021; Taiwo *et al.*, 2024).

While AI is proposed to have potential, its current application in construction remains scattered; existing results often show a focus on enhancing particular tasks (Nyqvist *et al.*, 2024a, b, Zhang and Jiang, 2024). For example, AI has showcased white-collar capabilities in specific functions like construction project risk management (Nyqvist *et al.*, 2024a, b), or blue-

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collar capabilities like the use of AI-supported robotics in solar module installation (AES, 2025). While these results can seem impressive, they are limited to narrow inspections of AI utilization.

To grasp its full potential, the focus should shift from optimizing isolated tasks to reconfiguring the entire system encapsulated in a company's business model, which provides a framework for analyzing holistic, rather than merely isolated, change.

AI-driven general contractors' business models are largely missing. Past studies have covered business models and digital transformation (e.g. Abiouye *et al.*, 2021). Also, AI and business model innovation have been explored in wider literature (e.g. Ancillai *et al.*, 2023; Teng *et al.*, 2025), often emphasizing a reorientation toward data-driven services and network-like business organizing (Burström *et al.*, 2021). However, these fail to particularly capture the impacts of AI on a general contractor's BM in the near future (e.g. until 2030), utilizing grounded empirical methods to drive insights from real companies.

Therefore, the objective of this paper is to address the gap by answering the question: "What could an AI-driven business model for a general contractor look like?" An answer has the potential to provide a structured (i.e. by utilizing the Osterwalder business model canvas (Osterwalder and Pigneur, 2010)) and timely overview of what an AI-driven business model is and is not, valuable for industry and academic actors to extend from.

To achieve an answer, the study employs a qualitative, multi-stage action research-oriented design. This approach begins with a literature review and BM preparations for two in-depth collaborative workshops with a Finnish general contractor, Jatke and their internal executive-level strategy work, to co-create an initial business model. This model is then refined and validated through engagement with 25 experts from 20 companies to capture broader perspectives and produce a transferable AI-driven BM for general contractors.

This paper is structured to guide the reader through our research process. Beginning with a literature background section to provide context for the study. Next, the research details the research design and methodology, outlining a three-phase empirical study. The following section presents the key findings, including an in-depth look at the final business model. The research then discusses the implications of the research before concluding with a concise summary of the publication.

2. Literature background

AI is a term for technologies that resemble human intelligence processes, while its subset, generative AI, creates novel content from existing data (Sheikh *et al.*, 2023; Sengar *et al.*, 2024). Fueled by significant and growing global investments (Statista, 2024), AI capabilities have been advancing at a significant pace (Maslej *et al.*, 2025). Current AI models have started to outperform humans in a variety of domains, from medical diagnostics (Goh *et al.*, 2024) to Go (Silver *et al.*, 2016), poetry (Porter and Machery, 2024) and achieving impressive results in scientific reasoning benchmarks (Epoch AI, 2024). The speed of AI capabilities growth thus positions it as a technology that can disrupt businesses across fields (Maslej *et al.*, 2025).

Research has often presented AI as a tool for optimizing discrete tasks (Abioye *et al.*, 2021). Common applications include doing tasks in the digital world (i.e. white-collar-oriented tasks), such as preparing documents or analysis, applicable in the construction industry context in cases like chairman and secretary tasks, communication and situational awareness improvement and data analysis and improvement (Nyqvist *et al.*, 2024a, b).

Additionally, combining AI with robotics allows for the completion of tasks in the physical world (i.e. blue-collar-oriented tasks). Examples of specialized construction robotics include TyBOT, which is used for rebar tying (Advanced Construction Robotics, 2025) and elevator installation robots, such as Schindler's Robotic Installation System for Elevators (Schindler Group, 2025). These examples highlight the current possibilities of robotics, which could be easily shadowed by the future possibilities of general-purpose robotics driven by AI (e.g. see simulation training (Zhou *et al.*, 2023; NVIDIA, 2025) and low-cost robotics (Chi *et al.*, 2025)).

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Although recent advances in AI have offered some hope for the future of the construction industry, construction companies still tend to operate within previously established operational paradigms, and as a toolbox (i.e. a series of tools to improve existing operations) rather than a large-scale disruptor. Such a tool-oriented perspective contrasts with the impact of past general-purpose technologies (e.g. electricity), which did not just enhance prior work but fundamentally transformed the modus operandi. Just as steam and electricity nudged the shift from an agrarian to an industrial society (Backhouse, 2023), the potential of AI may lie in a paradigm shift toward a post-human-dominated cognitive and manual work era, a transformation that a simple toolbox approach fails to envision.

Looking beyond the construction sector, literature claims that AI is a large driver of business model innovation (Ancillai *et al.*, 2023). Studies emphasize a reorientation toward data-driven services (Antai *et al.*, 2025). AI is also seen as enabling mechanisms such as digital platforms and novel ecosystem structures through network-like business organization (Adner, 2017; Gawer, 2022). This also introduces mechanics like lock-in (Han, 2019) and network effects (Chang *et al.*, 2019).

In order to move beyond the toolbox approach, it is necessary to distinguish between pre-2023 AI and the modern landscape. Historically, AI in construction was used as a narrow “point solution” for specific tasks (Abioye *et al.*, 2021). In contrast, generative AI now operates as a broader, more general-purpose technology (Eloundou *et al.*, 2023; Sajadieh *et al.*, 2026). With its new agentic capabilities, AI is shifting from being an analytical add-on to becoming a novel actor within human-dominated ecosystems (Sajadieh *et al.*, 2026). It has the potential to fundamentally alter the business models of general contractors (Massenkoff and McCrory, 2026). Thus, this study focuses particularly on the technological landscape of the post-2023 era.

Furthermore, similar reasoning distinguishes between “AI-driven” and “data-driven” approaches. While data-driven methods often rely on quantitative, number-based analytics, AI-driven models process unstructured documents and texts to generate knowledge, make decisions and perform autonomous actions, making “AI-driven” a more appropriate term in the current era.

The potential for new revenue streams, such as AI-as-a-Service (AIaaS), signifies a fundamental shift in the contractor’s value logic, which can be understood through the theory of servitization (Baines *et al.*, 2017). This transition involves adding services to core offerings, moving from one-time, project-based revenue to recurring models. For project-based firms, this extends beyond post-delivery maintenance to include value-added services in pre- and post-project phases. The advent of AI and other digital technologies accelerates this trend, leading to digital servitization, where data from a core process becomes the basis for new, scalable service offerings.

The shift to an AI-driven business model can be understood as a deliberate exercise in business model innovation, defined as designed, novel changes to a company’s mechanisms for creating, delivering and capturing value. This requires adopting new tools, but also poses an organizational challenge related to the novelty. A company’s success in this transition depends on its dynamic capabilities, the ability to sense new technological opportunities, seize them by revising business models and continuously reconfigure internal resources to adapt to the changing landscape (Teece *et al.*, 1997).

This need to sense, seize and reconfigure through dynamic capabilities confronts a significant obstacle in the construction industry. The prevailing business model for general contractors is project-centric and traditional, rooted in competitive bidding and the coordination of clients, designers and implementers. This established structure, while debatably effective for discrete projects, inherently lacks the agility required for fundamental business model innovation (i.e. due to inertia of industry norms). Consequently, the industry has primarily experimented with AI as a tool to optimize isolated tasks rather than undergo a disruption (Zhang and Jiang, 2024).

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Finally, while literature highlights AI's potential for isolated task optimization, breakthroughs and impacts in the construction industry remain relatively modest in impact (Massenkoff and McCrory, 2026). Arguably, AI is not currently driving the industry's core operations. There exists a lack of industry-wide, AI-driven potential capture, which underscores the topicality of research to define what an AI-driven general contractor business model could actually entail. Positioning this research to explore a plausible, near-future scenario for an AI-driven business model.

3. Research design and methods

This study is positioned in pragmatic scientific philosophy (Gillespie *et al.*, 2024), employing a qualitative, multi-phase design (see Figure 1 below) with an emphasis on action research methodology (Cassell *et al.*, 2018). This exploratory approach was chosen for its suitability in developing and refining a novel business model proposal (i.e. an AI-driven general contractor in a near-future scenario) within a real-world corporate context, allowing theory to be built directly from empirical data. The research process was organized into three main phases to ensure the final model was both theoretically grounded and practically relevant.

In Phase 1, the work began by establishing a conceptual baseline through a focused review of recent peer-reviewed scientific articles and industry sources. Key themes in AI adoption, business model innovation, business ecosystem research, platform economics and servitization were identified. Rather than seeking to produce standalone literature-based results, this phase aimed to structure a preliminary analytical template using Osterwalder and Pigneur's business model canvas (Osterwalder and Pigneur, 2010). To populate this initial canvas, the nine components were mapped against identified AI capabilities. Crucially, this preliminary version was not a definitive result, but an enabler designed to facilitate the subsequent workshops.

In Phase 2, these initial theoretical findings were then taken into an in-depth action research study with Jatke (a large Finnish general contractor with 482M€ turnover and 429 employees covering residential, commercial and renovation construction. As a main contractor, Jatke had

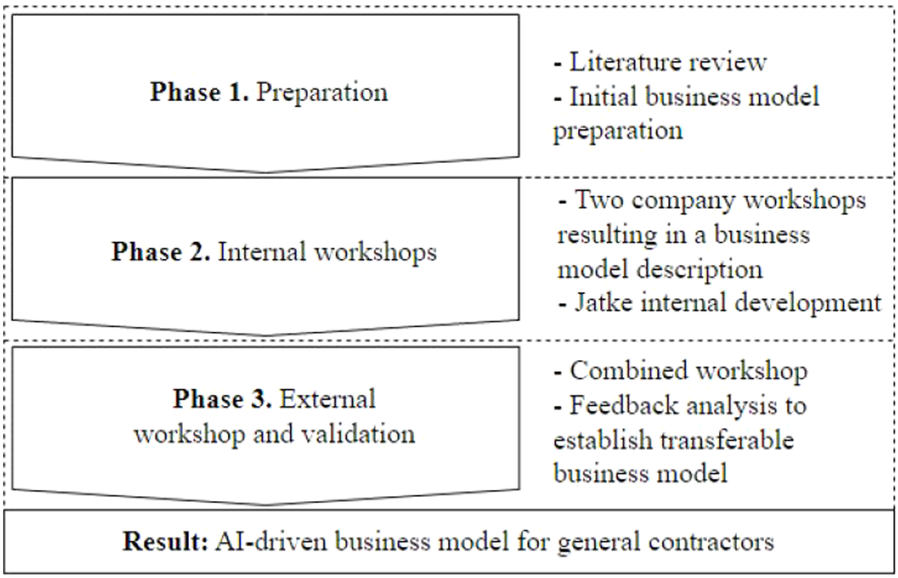

Figure 1. Research process

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2,800 subcontractors and a total of 10,000 individuals working on their construction sites 2024), selected for its active collaboration and focus on AI-driven business model development. The Jatke AI-driven business model was co-created through two 120-minute workshops with company executives, who subsequently conducted further internal strategy work to align the model's components with their operational realities. Thus, as an active stakeholder, Jatke provided the necessary real-world context for co-creating the proposed AI-driven business model to be utilized in the next phase.

Jatke was selected as a general contractor due to its appropriate inclination toward AI-driven development, including its existing data-driven operating infrastructure and ongoing strategy work on this topic. Appropriate maturity provided an empirical foundation. By utilising the company's internal development roadmaps and operational friction points, the research ensured that the findings were grounded in the real world rather than theoretical brainstorming alone.

In Phase 3, a combined workshop was conducted, where 25 expert participants representing 20 Finnish construction industry companies attended a 90-minute meeting, where the initial AI-driven business model, developed earlier with Jatke, was presented together with initial research findings. A series of questions (see Appendix for a full overview of the questionnaire) was issued to the 25 participants representing relevant industry stakeholders, such as company managers and development engineers. Following the questionnaire, an in-depth conversation was held with the participants.

The experts were selected using a convenience sample, targeting individuals with oversight of and technical expertise in, the digitalization of construction. While the reliance on a Finnish context limits statistical generalizability, the multi-stage validation ensures that the model reflects the shared logic of large-scale general contracting, supporting its contextual transferability to similar project-based ecosystems.

Empirical data was collected throughout the three phases. This dataset consisted of workshop memos, email correspondence and free-text questionnaire responses from industry experts. The data was analyzed using thematic synthesis with the nine components of Osterwalder's business model canvas as an *a priori* analytical frame. The research open-coded the workshop's free-text responses and iteratively grouped codes into emergent themes, which were then mapped to the relevant canvas components to ensure the proposed business model is grounded in the data.

Responses were allowed to be multi-coded when they addressed several themes; consequently, the "count" values in Table 2 refer to the number of coded mentions rather than unique respondents. It is important to clarify that these counts represent the number of times a theme was raised in the free-text responses, rather than representing a total percentage of support. Following the questionnaire, an in-depth conversation was held with the participants, where these emergent themes were discussed and validated more broadly among the 25 experts. The research also captured explicit peer endorsements recorded as "+1" in the raw data and reported these as "(+x)".

Thus, the findings section presents the results of the multi-phase research process (Figure 1). Each phase provides empirical grounding. Phase 1 establishes the initial structural components based on theory, Phase 2 captures insights from the case company Jatke and Phase 3 refines the model using broader industry feedback. The findings section focuses on the final outputs; e.g. the preliminary business model from Phase 2 is withheld from publication due to company-specific competitive restrictions. Consequently, the study showcases the three final artifacts derived from this iterative empirical validation: (1) a transferable, AI-driven business model (Table 1), (2) a conceptualization of the AI-driven general contractor as an ecosystem orchestrator (Figure 2) and (3) a framework for business model evolution (Table 3).

4. Results

The findings suggest that AI will primarily enable incremental improvements across the general contractor's core processes, including bidding, procurement and project

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Table 1. AI-driven business model for general contractors with key operational focus on bidding, procurement and implementation

Business model component	Key finding(s)
C1: Customer segments	AI does not fundamentally change a general contractor's broad customer groups, but it enhances how they are served. As AI models become more capable of providing fine-grained customer analysis, they can identify niche segments (e.g. sustainability-focused clients) within existing customer groups. A key strategy is to segment customers based on their digital maturity and willingness to share data. This allows for the offering of tailored service levels and the use of data for purposes such as training AI systems or providing building life-cycle services. High customer digital maturity also creates the foundation for offering more AIaaS. When real estate developers have access to broader market analysis, it lowers the barrier to entry for new markets and increases customer diversity
C2: Value propositions	Enhancements to a contractor's core value proposition are happening: e.g., delivering higher-quality, cost-effective projects through data-driven predictability, improved coordination and knowledge transfer, resource optimization and verified environmental, social and governance outcomes. While value is primarily created during construction, it can be extended across the asset's lifecycle. Also, effective data use enables a shift to strategic partnerships. The contractor can offer clients early access to custom AI systems built on its data pool, helping them in their planning phase and securing the relationship much sooner
C3: Channels	Channels focus on two key areas. First, improving the sales process by using AI agents to research bid requests, which improves offer quality and allows for hyper-personalization; the use of AI for discovering potential clients and partners will also become more widespread. Second, creating a new channel for early engagement by giving clients direct access to the contractor's customized AI systems, which creates a stronger lock-in effect. During the project, these are complemented by platforms for collaboration, all integrated to support decision-making and to serve as an information source for learning across cases, enabling network effects. While interaction with the client may be limited during the bidding process, interaction with a contractor's AI may be seen as a novel, unrestricted channel
C4: Customer relationships	Some transformation from transactional to continuous, data-driven partnerships starts to occur. Using AI tools, the contractor can engage in active co-creation much earlier in the project phases. Contractor AI can answer client questions anytime, anywhere, between the designated meeting schedules or outside of contractual obligations. The role evolves from a mere executor to an advisor, using general contractors' data to exceed standard AI solutions' capabilities. These lower-barrier and extended relationships are built on trust, which is fostered through the transparent and ethical use of AI
C5: Revenue streams	An AI-driven model's primary near-future impact is not to revolutionize a contractor's earning logic, but to enhance the efficiency and profitability of the current project-based business. By improving productivity, AI boosts competitiveness in traditional bidding and increases profit margins on projects. Secondarily, this new capability and the data collected open the door to potential complementary revenue streams. These can include AIaaS consulting or subscription-based services, which support the core business
C6: Key resources	The existing key resources remain. When it comes to AI-driven solutions, the new resource is not just a single technology, but rather the organizational capability to manage change. This is built on a foundation of strategically-governed data, specialized and continuously trained personnel and custom AI solutions like integrated agents. At the very least, this data will be used for information retrieval, even if it is not used for model training. Critical intangible assets, including change management skills, an ethical framework for responsible AI, a trusted brand and partnerships to complement in-house expertise

(*continued*)

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Table 1. Continued

Business model component	Key finding(s)
C7: Key activities	An AI-driven model enhances, rather than replaces, a contractor's traditional activities like bidding and procurement. While the core activities remain, many tasks, such as gathering product data, can be automated or replaced by AI, freeing up professionals like site engineers. Success requires new, continuous processes. These include managing the AI model's lifecycle and company data, and integrating AI with core tools like building information modelling. This framework should be supported by functions like AI-enhanced research and development, along with critical enablers: continuous staff training, proactive cybersecurity and regular ethical audits. To transform these internal capabilities into AIaaS, these back-end functions need a new front-end interface, similar to what is used in application development
C8: Key partners	Partner network changes by both deepening existing relationships and requiring entirely new connections. Traditional partners like subcontractors and designers are enhanced through shared data and platforms. New partners include technology and data providers, programmers, innovation hubs like research labs and startups and specialists in ethical auditing and cybersecurity. Active participation in the wider industry ecosystem and co-development with clients are also seen as valuable
C9: Cost structure	Core cost structure remains largely unchanged, still dominated by labor, materials, subcontracting and central office operations expenses. However, the introduction of AI is expected to streamline or replace work processes, leading to potential savings in existing key costs. A new cost layer emerges for AI and data solutions. This includes initial investments in technology, specialist recruitment and integration (i.e. upfront costs), followed by ongoing costs for maintenance, data governance, continuous staff training and ethical oversight (i.e. maintenance costs)

implementation in the near future. In addition, there is the potential for new offerings. These consist of customized AI tools and agentic solutions built upon proprietary data from the contractor's key operations, which could be offered to other industry actors. Next, the key result, an AI-driven general contractor business model, is presented in a modified Osterwalder business model canvas in Table 1. This Table represents a synthesis, combining theoretical basis drawn from the literature in Phase 1 with empirical findings and practical feasibility validated during the Phase 2 and 3 workshops.

The initial model focused on internal process optimization, treating AI, e.g. as a computational tool for cost estimation and scheduling. However, Phase 2 workshops shifted the focus toward strategic data positioning. It became more evident that the contractor's primary strength lies in its role as a data owner during the construction phase. Consequently, the model evolved from task-specific automation toward a platform approach where proprietary data, e.g. prevents "project amnesia" and supports decision-making.

Transitioning to the final model (Phase 3) involved refining "servitization" through expert validation. While earlier versions viewed AIaaS as a near-term revenue driver, feedback repositioned it as a long-term opportunity contingent on data traceability and governance standards. Furthermore, the value proposition sharpened from general ESG claims to verifiable outcomes, such as automated environmental certification. This iterative process ensured the model reflects a realistic pathway from an incremental toolbox toward a transformative, ecosystem-oriented role.

The business model presented in Table 1 was refined and validated through a workshop with 25 industry professionals. To transparently illustrate how this empirical data informed the model, Table 2 synthesizes the key themes that emerged from the discussion. Table 2 is structured around three core questions posed to participants (see Appendix) regarding AI's near-term potential, the realism of servitization and new ecosystem partnerships. It

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Table 2. Key themes from the industry workshop and mapping to business model components (derived from 25 respondents' feedback)

Question and focus area	Themes identified from feedback	Count	Representative quote (translated)	Business model mapping
Q1: Near-term AI potential	Tendering and risk analysis: Using AI to parse proposals, check contract interfaces and identify risks	4	"Check contract interfaces and exceptions with AI."	C2, C7
	Knowledge management: Improving data/document use and learning between projects	4(+1)	"Improve use of project documentation during construction."	C6, C7
	Project execution and quality: Automating on-site supervision and quality control	2(+1)	"Automate supervision and raise quality."	C7
	Disruptive models: Unbundling procurement of labor/materials; shifting competition to customer experience	2(+4)	"Separate materials and labor; logistics becomes decisive."	C2, C7, C8
Q2: Realism of AIaaS	Skepticism and barriers: Concerns over data privacy, competitive advantage and the limited value of single-firm data	3	"The data from one operator is ultimately very thin . . . who will boldly utilize information paid for by someone else?"	C5, C6
	Conditional optimism: Feasible if quality, traceability and maintenance are guaranteed	4	"Realistic if quality metrics, traceability and maintenance are guaranteed."	C4, C5
	Internal focus first: View AI primarily as a tool for internal productivity gains before external sales	3	"I currently see AI services as an internal productivity leap for companies."	C5, C7
Q3: New ecosystem partners	Data and AI Specialists: Need for partnerships with data analytics and AI expert firms	2(+1)	"Data analytics and AI expert companies will become partners for construction companies."	C8
	Technology and Logistics Providers: Importance of data platform providers and JIT logistics operators	2	"Data are definitely key, but, e.g. logistics operators will become more diverse."	C8
	New Strategic Alliances: Deeper partnerships with clients, research labs and certification bodies	2	"Research institutes, certifiers, labs, component manufacturers . . . "	C8

summarizes the most important points, clarifies the level of consensus for each theme, provides a representative quote and explicitly links each finding to the corresponding business model component (e.g. C7 key activities), thereby grounding the conceptual framework in direct industry perspectives.

The workshop confirmed that AI's near-term impact will concentrate on enhancing core operational activities. The most frequently cited potential was in improving tendering and contract quality assurance through the semi-automated parsing of documents and comparison of bids and risks. Participants also emphasized AI's value in enabling stronger knowledge reuse between projects and the partial automation of on-site execution and quality controls, reinforcing the focus on incremental efficiency gains.

Beyond these core enhancements, a minority of participants put forward strongly supported views on more disruptive changes. One key idea was that AI could enable the unbundling of

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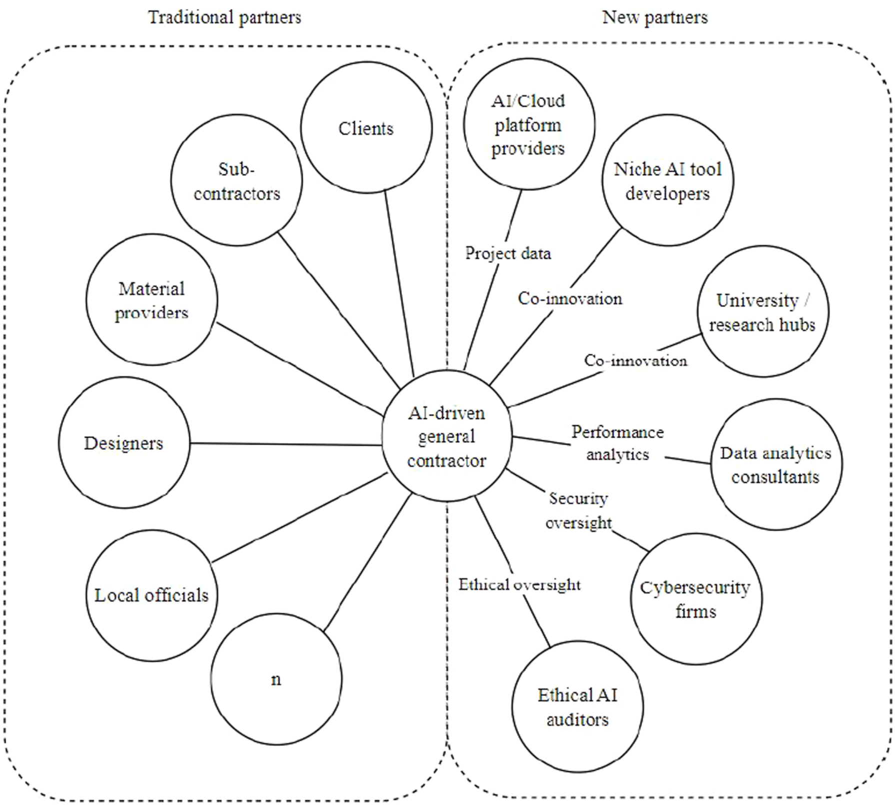

Figure 2. The AI-driven general contractor as an ecosystem orchestrator

procurement, which would elevate the role of Just-in-Time logistics. Concurrently, there was a belief that the basis of industry competition could finally shift away from price and toward delivering a superior customer experience.

When considering the shift to servitization, industry opinions were mixed regarding the feasibility of AIaaS by 2030. Its adoption was seen as contingent on clear data quality metrics, traceability and robust maintenance agreements. A significant barrier identified was that single-firm datasets are often insufficient, leading participants to suggest that centralized models with firm-specific add-ons are a more viable path forward.

This evolving business model requires new partnerships beyond the traditional supply chain. Respondents identified a future ecosystem that includes AI and data specialists, technology platform providers, logistics orchestrators and assurance actors like certifiers and labs. This feedback led to a refinement of the business model, strengthening the definitions of key activities and partners while positioning AIaaS as a complementarily service with preconditions for adoption.

The transition toward an AI-driven model is seen to be affected by several industry-specific barriers. The fragmented nature of the construction ecosystem obstructs the holistic data integration necessary for AI to deliver its full benefits. Many companies also exhibit low digital maturity, and a project-based mindset often prioritizes short-term execution over long-term investments in technology. Workshop findings further highlight that concerns over data ownership and competitive sensitivity are significant barriers to AIaaS adoption. Practitioners noted that single-company datasets are often too “thin” to be effective, suggesting a need for

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Table 3. Comparison of business models

Business model	Primary value proposition	Value capture mechanism	Revenue timing	Customer relationships
1. Traditional project management	Delivery of a physical asset on time and on budget	Fixed price or cost-plus contract	One-time, upon project milestones	Transactional
2. AI-enhanced project execution (internal efficiency focus)	Increased cost and quality competitiveness through AI-driven internal process optimization	Higher margins on traditional contracts due to improved productivity and cost savings	One-time, upon project completion, with enhanced profitability	Primarily transactional, but enhanced quality may strengthen the relationship
3. AI-based services for a project client (added-value services for a project client)	Enhanced project outcomes through data-driven predictability, resource optimization and verified ESG results offered to the client during the project	Additional fees for premium services or included as a value-add to secure strategic partnerships	During the project, tied to the delivery of specific value-added services	Evolves from transactional to an advisory partnership for the project's duration
4. AIaaS (project independent data service)	Actionable insights and performance outcomes derived from the contractor's proprietary data, available to any external party (e.g. developers, consultants and manufacturers)	Subscription, usage-based, or outcome-based fees	Recurring, independent of project lifecycles	Continuous partnership

centralized model governance combined with company-specific adapters to overcome reluctance to share proprietary data.

As a result, many core components of the general contractor's business models are initially enhanced rather than replaced. For instance, value propositions are augmented with data-driven predictability, but the core offering remains the delivery of cost-effective projects. Likewise, the cost structure remains largely unchanged, with AI-related expenses emerging as a new layer.

Scaling benefits from AI across an entire company appears to be seen as a slow process, requiring a deliberate commitment from leadership to invest in new skills, technology infrastructure and management systems that formally integrate AI into daily work.

The integration of AI into a contractor's operations will be shaped by its "jagged technological frontier," where it excels at some tasks but fails at others. Results suggest the most effective model is not replacement, but collaboration, where AI acts complementary to generate a "first draft" for tasks like project planning, which human experts then refine and validate. There is also an implication that the white-collar jobs most prevalent in a contractor's office are the ones exposed to AI-driven task transformation, creating a need for reskilling.

A key competitive advantage emerges from creating specialized AI agents trained on or backed by a contractor's proprietary data. Developing these custom tools requires initial investment in technology and personnel, followed by ongoing costs for data governance and model maintenance. However, this tailored approach produces agents that can arguably outperform generic AI (e.g. standard ChatGPT). These capabilities could provide a competitive advantage in a market where small advantages are decisive. When rival firms operate under comparable business models, projects are often won through marginal price cuts. In that setting, small gains in operational efficiency become decisive. The company that can learn fastest and refine its routines secures an edge that price alone cannot match.

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The transformation of the business model could happen by the general contractor's evolution from a project manager to an ecosystem orchestrator. This shift is visualized in Figure 2. The contractor sits at the hub connecting the company to new ecosystem partners, e.g. AI platform providers, data analytics consultants and ethical AI auditors. Then the value exchange is no longer linear but multi-directional, involving flows of project data, performance analytics, co-innovation and ethical oversight, illustrating a change from a supply chain to a value ecosystem where new partners are more prevalent.

This orchestrator role could extend beyond project delivery, positioning the AI contractor as a central hub also for the building's entire lifecycle. Thus, the contractor could integrate data streams from various ecosystem partners to manage the building as a holistic system. This enables the offering of continuous, AI-driven lifecycle services (e.g. building as a service offerings), transforming the business model from a transaction to a long-term partnership, with recurring revenue streams and network effects through data cumulation.

A key finding was also the shift toward customer-driven personalization through AIaaS, where clients directly query the contractor's data, improving efficiency over the contractor proactively addressing all questions. Furthermore, segmenting customers by their AI maturity allows for tailored service levels, from basic reporting to custom integrations, creating a more personalized approach to client relationships.

Elaborating on the potential of AI-driven services, the workshop highlighted a disruptive model where AI could enable the separation of labor and material procurement. In this scenario, AI systems would perform high-quality project planning and create detailed work-breakdown structures. This would allow for the procurement of labor through digital platforms, connecting individual tradespeople to specific tasks, a model where workers increasingly become entrepreneurs. Concurrently, material procurement could be optimized with greater accuracy, enhancing the role of Just-in-Time logistics. Such a platform-based approach would fundamentally reshape the general contractor's role from a manager of subcontracts to an orchestrator of a dynamic, on-demand workforce and supply chain. However, such a change was not commonly seen as imminent (i.e. not likely to happen by 2030) by the workshop participants or within Jatke management.

The shift in revenue streams (C5) is tangible evidence of business model innovation, explainable through the lens of servitization. The contractor can move from capturing value one-time in a project-based transaction to creating recurring revenue throughout AIaaS. The following Table 3 provides a comparison of the value logic between four business model variants: (1) traditional project management, (2) AI-enhanced project execution, (3) AI-based services for a project client and (4) AIaaS.

While the data broadly supported the shift toward an AI-driven business model, outlier opinions questioned the general contractor's credibility as an AIaaS provider, arguing that global tech giants are better positioned to orchestrate the digital ecosystem. Furthermore, contradictions surfaced regarding data ownership and liability as clients may refuse to pool proprietary cross-project data for, e.g. AI agent use. Also, unresolved accountability for AI-generated errors demonstrates that evolving into an ecosystem orchestrator is a contested shift, necessitating data governance and "human-in-the-loop" oversight.

In summary, to address the contradiction between viewing AI merely as an operational "toolbox" and recognizing its potential to transform general contractors into ecosystem orchestrators, this research posits that AI's impact is a continuum. This evolution is structured across the distinct maturity phases outlined in Table 3. Business model 1 with low or no AI adoption is a common reality in construction companies, as evidenced by the low adoption and low identified potential by industry independent researchers (Massenkoff and McCrory, 2026), as well as the future oriented replies in the surveys and workshops. Business model 2 is the foundational, incremental phase, in which localized AI primarily serves as an internal toolbox to enhance efficiency and optimize existing processes. Business model 3 is transitional; here, human-AI hybrid teams begin to reshape traditional roles and enable value-added client services. Finally, business model 4 reflects a fully transformative shift. In this

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final phase, the general contractor moves beyond its traditional role to offer servitized, project-independent solutions such as AIaaS and takes on the role of an ecosystem orchestrator.

5. Discussion

The objective of this study was to determine what an AI-driven business model for a general contractor could look like. The study contributes to the field by applying servitization theory to the project-based context of the construction industry through the lens of AI. The study provides empirical evidence that general contractors can transition from a transactional, project-delivery model to a servitized one that offers new, data-driven services like AIaaS. The findings, as illustrated in Table 3, show that servitization in construction is not simply about adding post-sale maintenance, as is common in manufacturing. Instead, it involves creating entirely new value streams from proprietary project data, altering the industry's traditional value capture mechanisms. This extends the foundational work of scholars like Liu *et al.* (2022) by providing a concrete, empirically-derived model of digital servitization within this unique industrial setting.

Furthermore, the findings indicate that general contractors' business model transformation is not a single, radical shift but likely a gradual pathway involving gains in operational efficiency alongside the creation of new data-centric services. It is anticipated that industry ecosystem-wide inertia and cultural resistance will temper the pace of adoption, making a radical business model change cumbersome.

To discuss further, this section is structured as follows. First, the theoretical implications detail key findings and compare them with existing literature. Second, the practical and managerial implications provide insights and propose solutions for industry practitioners. Third, research limitations are elaborated and finally, future research avenues are proposed.

5.1 Theoretical implications

Rather than claiming the development of a novel general theory, this study is positioned as applied research that contextualizes existing theoretical frameworks within the unique parameters of the construction industry. First, this research demonstrates how servitization theory can be applied to the project-based context of the construction industry. Although servitization has been widely studied in manufacturing, particularly in relation to digital servitization (Paiola *et al.*, 2024; Li *et al.*, 2024), its practical application in construction is still in its early stages and could benefit from the systematic frameworks presented here (Liu *et al.*, 2022). This study provides empirical evidence that general contractors can adopt servitization strategies and transition their business models from transactional, project-based contracts to recurring revenue models.

Transition toward recurring revenue models is made possible by the emergence of new, data-driven offerings such as AIaaS. This finding resonates with research on digital platforms, which highlights that digital technologies enable enterprises to "unlock data value" and create new services (Jia *et al.*, 2024). This study demonstrates that this transition is not just about adding services but, as argued by Liu *et al.* (2022), it involves a fundamental shift in the value-adding process itself. It moves from an "activity-oriented" approach to a "demand-oriented" one, where value is co-created with the customer throughout the entire lifecycle of the building, paving the way for recurring revenue streams and a more sustainable business model.

Second, this study contributes to business ecosystem theory (Moore, 1993; Jacobides *et al.*, 2018) by illustrating how a general contractor can evolve into an ecosystem orchestrator. The findings, consistent with Tan *et al.* (2025), detail a shift to a multi-directional ecosystem where the contractor facilitates data flows between clients, subcontractors and new partners like technology providers and ethical auditors. This provides a conceptual model for a networked, value-creating system previously under-theorized in the fragmented construction context (Nyqvist *et al.*, 2024a, b).

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Therefore, the business model evolution is not a simple technological upgrade but, as Wang *et al.* (2025) suggest, a complex process demanding organizational readiness and dynamic managerial capabilities like "digital ecosystem building." The findings, like those of Nguyen *et al.* (2026) on corporate social responsibility and business model innovation, reinforce that fostering collaborative partnerships and embracing this orchestrator role is a strategic necessity for survival and growth, especially in an industry characterized by fragmentation and resistance to change. Because trust is fundamental in client relationships, leaders should develop ethical AI guidelines (as also reflected in the proposed model's key resources) and communicate how AI is used in decision-making. Demonstrating transparency in AI-driven decisions will reassure clients and employees, smoothing the adoption.

Finally, the findings align with and extend the theory of dynamic capabilities (Teece *et al.*, 1997), showing that an AI-driven business model requires firms to sense, seize and reconfigure resources. The empirical findings, such as the emphasis on new partnerships with data specialists and the need for continuous data management processes, provide concrete examples of the micro-foundations required for AI-driven transformation in construction. These findings resonate with recent literature that has specified dynamic capabilities for digital transformation to include digital ecosystem building and strategic agility (Wijayarathne *et al.*, 2024). Our model provides an integrated view of how sensing (e.g. using AI to identify niche customer segments), seizing (e.g. developing and launching an AIaaS offering) and reconfiguring (e.g. building new data governance structures) manifest in this specific industrial and technological context.

This perspective is supported by Shi *et al.* (2025), who discovered that generative AI has a positive impact on knowledge-based dynamic capabilities, especially knowledge integration and absorption. These findings confirm that developing expertise in these areas is a strategic necessity for long-term success. Li *et al.* (2025a, b) further support these findings, highlighting that the dynamic construction environment makes seizing and reconfiguring capabilities more critical than sensing for achieving resilience and sustainability. These results suggest that AI-driven general contractors must become ecosystem orchestrators, moving beyond a toolbox approach. This evolution is similar to what Li *et al.* (2025a, b) refer to as dynamic knowledge management, in which knowledge is continually reconfigured to align with strategic objectives, paving the way for true positive disruption.

5.2 Practical and managerial implications

For general contractors, the co-developed model offers a practical guide to link short-term wins with long-term digital growth. This involves starting with low-risk pilots and building alliances before scaling ideas, a crucial strategy given the industry's fragmented nature. Managers must also critically evaluate AI tools, as their proposals may lack real-world context, a limitation that practitioner-led research helps to address. The slow pace of change at established firms can make them vulnerable to faster, more agile competitors.

This vulnerability is particularly acute given that an individual contractor's proprietary data are often considered too thin to develop effective, large-scale AI models. An agile new competitor, such as a software or platform company, could aggregate data across multiple projects and firms. This would allow them to build a more robust dataset, potentially enabling them to develop and offer superior AI-driven services that outperform those of any single, slow-moving incumbent.

For a construction company that is successfully aggregating its own internal proprietary data, this also presents a new business path. Given that many fail to achieve this (Challapally *et al.*, 2025), a company that has succeeded could productize its internal data aggregation and offer it as a service. This turns a defensive move into an offensive one, opening the door for a new type of AI-driven business.

Interestingly, these efficiency gains do not necessarily reduce workloads. According to Jevons's paradox, when AI enables companies to achieve the same results with fewer

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resources, unit costs decrease. Lower costs can make previously marginal projects viable. This new demand may offset the labor saved and increase the total volume of work. However, individual occupations might face disruption, or even extinction, due to more capable solutions replacing them. Thus, managers must also invest in reskilling programs, training project managers and engineers in AI-augmented workflows, to address the workforce disruption that AI tools may cause. Cultivating a culture of continuous learning will help staff embrace AI as a collaborator rather than fear job loss.

Managers should prioritize using AI for knowledge management to overcome “project amnesia” by systematizing project data and documentation. This aligns with the concept of dynamic knowledge management, where AI is used to strategically reconfigure and reuse information. This approach builds a comprehensive, searchable and reusable knowledge base that informs future decisions, moving beyond simple task automation to create lasting organizational value.

For example, a forward-looking general contractor might start by building a central “data lake” of project information and use an AI to help project teams query past lessons (a practical step toward dynamic knowledge management). This addresses the chronic issue of project knowledge siloing.

Furthermore, applying AI models in collaborative delivery methods, like integrated project delivery, can present structural hurdles. Their temporary nature complicates data segmentation and security between partners. Consequently, custom AI integrations for one-off projects can become complex and costly, often leading to continued reliance on manual data management. Even, e.g. when collaborative models utilize building information modeling as a shared data lake, technical limitations can persist. AI capabilities remain partially unproven in matching the specific workflows human project teams prefer. Such practical barriers require general contractors to carefully account for these limitations when positioning themselves within the broader digital ecosystem.

It is essential for companies to strategically position themselves within the evolving ecosystem. The traditional partner network is expanding to include data analytics and AI specialists, research institutions and technology providers. Managers should actively seek out these new alliances to become an “ecosystem orchestrator,” facilitating a multi-directional value network where data are a primary currency. Building strong internal competencies in data governance and security is a prerequisite for offering new services like AIaaS.

Finally, managers must reconsider their business models to prepare for disruptive scenarios, and maybe aim to disrupt themselves and cannibalize their existing business processes. This includes exploring a model where AI platforms could unbundle labor and material procurement, fundamentally reshaping the contractor’s role. Rather than simply reacting to these changes, managers should proactively explore new, platform-based solutions to lead the transformation and embrace a future where efficiency and a superior customer experience become the new competitive advantage.

5.3 Limitations

This study recognizes limitations inherent in its qualitative, action-research design within a Finnish context. The findings, though transferable, should be viewed with caution as they may not be entirely generalizable to other markets. This is because the research is based on a limited dataset from one case company and a single validation workshop with 25 participants from 20 Finnish companies. Furthermore, as shown in Table 2, the written mentions for specific themes ranged from two to four instances. While this reflects unprompted qualitative responses rather than a lack of consensus, and these themes were subsequently validated during the in-depth conversation held with the participants, this reliance on a subset of active written responses implies that the model’s validity is grounded in qualitative expert consensus rather than statistical significance. This sample size and regional focus limit the ability to draw broad conclusions about the entire global construction industry.

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In addition to these sample size constraints, the selection of the workshop experts relied on convenience sampling within the local ecosystem, meaning the contextual transferability of the model to different international markets or regulatory environments remains untested. Furthermore, the validation process was confined to a single 90-minute session. While this format captured a cross-sectional expert consensus, it did not allow for longitudinal tracking or the systematic long-term reconciliation of conflicting views.

Furthermore, a key limitation lies in the study's scope, which did not quantify the scale of challenges such as inertia and skill gaps. While the presence of significant company-wide, and industry inertia was observed, the research did not measure the extent of this resistance. As a result, the study cannot definitively determine the level of effort required for successful implementation, and the identified challenges are based on qualitative insights rather than statistical evidence.

5.4 Future research

Future research should study the identified business model variants (see Table 3) across larger and more diverse international samples to test their generalizability. As this study is limited to a single national context, comparative research is needed to understand how regional factors, policies and differing levels of digital maturity influence AI adoption. This would provide valuable insights into the transferability of the model.

There is a clear need for deep-dive studies into the micro-foundations of this transition. Research should investigate how firms build specific data-related capabilities, manage data ownership and overcome the challenge of limited company-specific data. This would include exploring how AI can be used to drive knowledge integration and absorption across projects, transforming individual insights into a scalable organizational asset. Furthermore, longitudinal studies would be beneficial to track the actual implementation of these AI-driven business models over time.

And finally, looking beyond incremental gains, future research should explore disruptive scenarios. This includes the workshop-proposed model, where AI enables the unbundling of labor and material procurement, profoundly reshaping the contractor's role. Investigating the convergence of AI and robotics in this context would offer a complete paradigm shift, moving from human-led execution to fully automated, AI-driven operations within a new value-network ecosystem.

6. Conclusion

This paper puts forward an AI-driven business model that reimagines general contractors as data-driven ecosystem orchestrators. The model, developed through action research, reveals a dual impact: AI boosts internal efficiency while enabling new service-based revenue streams like AIaaS. The framework's main contribution is demonstrating how servitization and ecosystem concepts, common in other sectors, can be practically applied within the project-based construction industry to create new forms of value.

Ultimately, this research suggests that AI transition depends more on building dynamic organizational capabilities than on the technology alone. Success hinges on a firm's ability to adapt, govern data effectively and foster strategic partnerships. The proposed business model should therefore be seen as a foundational "toolbox" rather than an immediate revolution. This initial phase is essential for developing the necessary AI maturity for future, more disruptive changes.

While this study provides a conceptual blueprint, its findings are based on a specific context and would benefit from broader validation. Future research should test and quantify the model's impact across different markets and company sizes. Such work would help generalize the findings and provide a clearer roadmap for an industry on the cusp of a significant technological shift, moving from the AI as a toolbox to a truly transformative future.

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Appendix

Workshop questionnaire questions (translated to English)

Question 1. In which area or how do you see the greatest potential for changing the construction industry with the help of artificial intelligence (in the near future, 2025–2030)?

For example: Bid calculation and pricing, procurement and subcontractor network management, project implementation and monitoring (e.g. schedules and quality), knowledge management and learning between projects (combating "project amnesia"), activities causing widespread disruption (specify).

Question 2. The study suggests a shift toward servitization, such as selling artificial intelligence services (AIaaS) created from your own data to customers or other stakeholders. How realistic do you think this idea is by 2030?

For example, would you purchase access to an AI service trained with data from a construction company that would serve your projects or business?

Question 3. In the future, the main contractor may become an "ecosystem leader" that brings together new players in addition to traditional partners. Who do you see as the most important new partners for the construction industry in the ecosystem of the future?

For example: Technology and data platform providers, data analytics and artificial intelligence specialist companies, research institutes and start-ups, customers (in deeper data partnerships).

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