

The Critical Steps for Using AI: A Case Study from a Manufacturing Company

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Abstract. *AI adoption among Central and Eastern European manufacturers remains low. This paper reports the first phase of a case study in a Croatian mid-cap manufacturer of modular buildings. Drawing on recent literature, quality-management documentation and fifteen semi-structured interviews covering ten organisational roles, it maps where AI can support company processes and proposes a phased implementation framework that begins with governance and low-risk office applications. A TOE-based survey of 63 of 82 employees shows high intention to use AI but weak organisational readiness; trust and perceived market pressure are the strongest predictors of intention ($R^2 = .70$).*

Keywords. artificial intelligence, business value, technology adoption, TOE framework, modular construction, manufacturing mid-cap

1 Introduction

Over the past few years AI has crossed from pilot experiments into everyday use. Its effect on manufacturing performance is now measurable rather than speculative, yet adoption across Central and Eastern Europe has not kept pace. Drawing on the European Manufacturing Survey, Kovic et al. (2024) report that only 18.4% of manufacturers in Croatia, Slovenia and Slovakia run AI software in even one production area. What sets the adopters apart, they find, is readiness for Industry 4.0 rather than company size or position in the supply chain. More recent figures show movement but a persistent gap: by 2025 about 15% of enterprises in Croatia used at least one AI technology, up from about 12% a year earlier yet still below the EU-27 average of roughly 20% (Eurostat, 2025), and a 2025 survey of more than 3,200 SMEs across eleven CEE countries found that, while some three-quarters report using AI, only about a quarter do so at scale (AI Chamber, 2025). Construction tells a similar story. Reviews of modular and prefabricated

building argue that AI and robotics are needed to unlock the full advantage of industrialised production (Pan et al., 2022), and the arrival of generative AI and large language models (LLMs) has added a class of applications that companies can take up without heavy upfront investment (Ghimire et al., 2024; Ma et al., 2025).

The case examined here is one such company. It is a Croatian mid-cap manufacturer in the north-west of the country, with several decades of tradition in steel structures and modular buildings, and it now produces modular residential, educational, hotel and office units (E-houses among them), mostly for export to Germany and other west European countries. Its integrated management system is certified to ISO 9001, ISO 14001 and ISO 45001, and since 2025 it has been introducing lean management: 5S, the Last Planner System, Kaizen and visual management. Management is now weighing how to bring AI into its processes in a systematic way.

Three questions guide the study. The first, RQ1, asks which business processes of a modular construction manufacturer hold the most potential for AI support. The second, RQ2, asks how ready employees are for that step, read through the technology-organisation-environment (TOE) lens. The third, RQ3, asks what implementation path suits a manufacturing mid-cap that is adopting AI in the middle of a lean transformation: in what order, starting when, governed how, and with how much outside help.

The rest of the paper is organised as follows. Section 2 sets out what AI promises companies and why they adopt it. Section 3 turns to the more specific literature on AI in modular construction and on adoption in manufacturing SMEs. Section 4 describes the company and where it stands today, and Section 5 sets out the research design. Section 6 puts forward the preliminary framework, Section 7 presents and discusses the survey results, and Section 8 concludes.

2 The promise of AI for companies

The case for adopting AI rests less on the technology itself than on the value it is expected to create. Reviewing the literature on AI and business value, Enholm et al. (2022) sort that value into two kinds. The first is automational: AI takes over work that people would otherwise do. The second is informational and transformational: it sharpens decisions, products and ways of working. The same review adds a caution that runs through the rest of this paper, namely that the value never appears on its own. It is realised only when AI is matched with the right data, skills and organisational routines.

The first and most tangible promise is productivity. McKinsey's analysis of generative AI puts the prize at USD 2.6-4.4 trillion a year across the activities it examined, and about three-quarters of that value falls in a handful of functions: marketing and sales, customer operations, software engineering, and research and development (Chui et al., 2023). Field evidence is beginning to catch up with the projections. Studying 5,172 customer-support agents, Brynjolfsson et al. (2025) found that access to a generative-AI assistant raised the number of issues resolved per hour by about 15%, and the largest gains went to the least experienced staff, who in effect absorbed the know-how built into the tool. Qualitative work points the same way: in a study of Spanish firms, Mas-Machuca et al. (2025) describe how generative AI moves effort away from routine drafting and searching toward judgement and client-facing work, as long as employees are given time and clear guidance. For a manufacturer the equivalent gains sit not on the line but in the office and engineering work around it, from drafting and translation to searching documentation and preparing quotations. Recent evidence from smaller manufacturers suggests these office-side efficiencies are where AI pays off first (Turcic et al., 2025).

Quality and consistency are a second reason. An AI system applies the same logic every time and can screen far more cases than a person, so it cuts the errors and rework that build up in manual, repetitive work. In construction this is clearest in computer-vision inspection, where the technology already rivals manual checking on well-defined defects (Yevu et al., 2025). A third reason is better decisions, and better use of what a firm already knows. From 152 cognitive-technology projects, Davenport and Ronanki (2018) separate three things AI does for companies: it automates back-office processes, it draws insight out of data, and it engages with customers and employees. The firms that gain most, they observe, treat AI as a way to augment people rather than replace them, and they get there through incremental projects rather than 'moon shots'. A related benefit is the ability to hold on to institutional knowledge. A searchable, AI-supported knowledge base keeps the experience of departing staff

available to those who remain, which for many firms is a quiet but real source of value.

None of this follows automatically, which is the fourth and most important point. Mikalef and Gupta (2021) show empirically that performance comes not from buying AI but from an AI capability, a bundle of data, technical skill and organisational resources such as coordination and a supportive culture, which in turn raises organisational creativity and firm performance. How the technology lands inside a firm matters as much as the technology itself. Tracing the arrival of generative AI through organisational networks, Olmedo Mejia and Cvetkoska (2025) find that value appears only as roles, routines and responsibilities are renegotiated around the tool rather than bolted onto it. This fits the manufacturing evidence that readiness for Industry 4.0, not firm size, separates adopters from the rest (Kovic et al., 2024), and the broader finding that digital and innovation capabilities are the main drivers of AI adoption among European SMEs (Arroyabe et al., 2024).

These mechanisms take a particular shape in manufacturing and construction. Within manufacturing, real AI use concentrates in quality control, production-process management and maintenance. There, vision systems and predictive models cut defects and downtime, while the office and engineering functions gain most from language and search tools (Kovic et al., 2024). In construction the promise is twofold. On the production side it is machine vision and analytics; on the information side it is turning scattered technical documentation into something a system can read and answer questions about. Recent work shows large language models moving beyond classic business intelligence to process and summarise unstructured documents directly (Krcmar et al., 2025), precisely the capability a documentation-heavy modular manufacturer needs. The promise of AI, then, is not generic. It is strongest where a firm's particular work is bound up with information.

Against these promises stands a counterweight the same literature keeps raising. The gains do not arrive on their own. Beyond the technical and data barriers there is a human one: working with AI can itself become a source of stress and quiet resistance, which a recent bibliometric review flags as a fast-growing theme under the label of technostress (Zron, 2025). The practical implication is that the case for AI has to be made to a company's employees and not only to its management, and that adoption is as much a matter of preparation, of time, training and trust, as of technology. It is partly for this reason that the present study sets its analysis of processes alongside a direct measurement of how ready the workforce actually is.

A final reason is competitive, and it is as much about risk as opportunity. As AI spreads through an industry, early adopters accumulate data, skills and routines that later entrants struggle to copy. Those who wait, meanwhile, meet customers and partners who

increasingly take digital ways of working for granted. For an export-oriented manufacturer that pressure is immediate, and it turns AI from a discretionary investment into a condition for staying competitive. Taken together, these five reasons, productivity, quality, better decisions, capability-building and competitiveness, explain why companies are turning to AI. They also frame the question this paper sets out to answer: not whether the promise is real, but how a manufacturing mid-cap can realise it given its own processes and its own state of readiness.

3 Theoretical background

3.1 AI in modular and prefabricated construction

Work on AI in modular construction has expanded quickly. In a systematic review of 97 articles, Pan et al. (2022) organise the field along a concept-methodology-value scheme that runs from design through manufacturing and transport to on-site assembly, and they argue for introducing AI in stages along the value chain rather than as a single leap. Liu et al. (2024) survey its use in production, operations and logistics, and single out predictive scheduling and the optimisation of assembly sequences as the most promising avenues. Wang et al. (2025) sort AI-based robots in industrialised building manufacturing into four capability groups, namely cognition, communication, control, and collaboration and coordination, and map them onto five factory stages that include cutting, welding and forming. Their advice is to de-risk such investment with digital twins and to lean on transfer learning where volumes are low and variety is high. Quality control is where the evidence is firmest. Convolutional neural networks dominate, with artificial neural networks next, and productivity and safety are the recurring problem areas (Yevu et al., 2025), which is why machine vision is the most mature and least risky place to begin. A PRISMA review of generative design and optimisation in prefabrication maps four research trends against twelve obstacles, of which algorithmic complexity and data interoperability are the most serious (Rangasamy & Yang, 2025). In a more applied vein, Heredia Alvaro and Gonzalez Barreda (2025) show how a retrieval-augmented generation (RAG) system built on LLMs turns manufacturing documentation into working support for quality control.

3.2 AI adoption in manufacturing SMEs

A second strand treats adoption as an organisational problem. Within manufacturing, real use clusters in quality control, production-process management and maintenance, and every step up in Industry 4.0 readiness raises the likelihood of using AI by roughly

21% (Kovic et al., 2024). Sanchez et al. (2025) combine the TOE and diffusion-of-innovations frameworks, list ten obstacles facing SMEs, from access to data and a shortage of skills to cultural resistance, and lay out a six-phase roadmap. On a far larger sample of 12,108 European SMEs, digital capability turns out to be the main driver of adoption, amplified by innovation capability (Arroyabe et al., 2024). German data tell a similar story of early-stage adoption and a gap between how relevant firms believe AI to be and how much they actually use it (Ulrich et al., 2021). In construction specifically, the strongest pull for LLMs comes from the company level, from partnerships, in-house research capacity and staff training, while hallucinations, data security and the complexity of the domain hold use back (Ghimire et al., 2024; Ma et al., 2025). And, as upper-echelons research keeps showing, it is the engagement of senior managers that finally decides whether AI integration succeeds (Bevilacqua et al., 2025).

3.3 Lean management as an organisational foundation for AI

Lean management and digital technology are increasingly read as two sides of the same coin. Industry 4.0 tools reinforce lean practices and the reverse holds too (Buntak et al., 2019), and lean maturity is one of the building blocks in the Croatian model of the innovative smart enterprise (Veza et al., 2016). A lean transformation steadies processes, brings waste into view and grows a culture of continuous improvement (Womack & Jones, 1996), the very conditions the adoption literature ties to lower organisational barriers to AI. The influence runs the other way as well: AI can sharpen lean practice, whether by feeding predictions into the Last Planner System or by flagging the anomalies that trigger and on signals.

4 Case company and current state

In EU terms the case company is a mid-cap. It has outgrown the SME thresholds of 250 employees and EUR 50 million in turnover, yet it stays below the large-enterprise scale that, in EU usage, reaches up to about 3,000 employees (European Commission, 2025). Larger than an SME, it nonetheless shares many of the resource and skills constraints documented for smaller manufacturers, so the SME adoption literature remains the closest evidence base. The company works with modern CNC and robotic equipment for cutting, bending and welding steel, and with software for optimising sheet and plate yield. Its processes are laid down in an integrated quality manual and a set of procedures that cover sales and quotation, contract review, technical documentation, supplier approval, procurement and incoming inspection, production planning, in-process and final inspection, and internal

audit. Digitalisation, however, is patchy. Design and engineering rely on several CAD and 3D packages; administration and procurement run on an ERP system whose limitations are well known internally; and the shop floor still works largely on paper, supported by a single mobile application for quality.

As part of the lean rollout, fifteen semi-structured interviews covering ten roles were conducted in May 2026, from the general manager down to a line worker. Five problems came up again and again. Production is not planned at company level, so work stays reactive. Waiting is the largest single waste, with an estimated 30-35% of hours non-productive and about 30% of line tasks started without all of their preconditions in place. Technical and technological documentation arrives late or after the fact, and the resulting rework costs roughly EUR 100-1,000 a case. Material is ordered by hand and sometimes twice. And what the management system prescribes and what actually happens line up only about 49-60% of the time. These five problems are the backdrop against which the AI use cases are judged.

5 Research design

The work follows an exploratory single-case design (Cooper & Schindler, 2014) in three phases. The first analysed documents, including the quality manual, the procedures and the lean working instructions, alongside the fifteen interviews just described. The second mapped the AI use cases found in the literature onto the company's own processes, which is what produced the preliminary framework in Section 6. The third phase was an anonymous online survey of every employee who uses a computer and e-mail regularly, across seven departments: design and engineering; production preparation and technology; commercial and procurement; accounting; production; project management; and quality control. It ran in June 2026 on SurveyMonkey. Invitations went to 82 addresses, and 63 employees completed the questionnaire in full, a response rate of 76.8%. The instrument has 27 statements answered on a seven-point Likert scale (1 = strongly disagree, 4 = neither agree nor disagree, 7 = strongly agree). These are grouped into six blocks, namely usefulness and ease of use (B1), trust in AI (B2), organisational readiness (B3), the environment of market and regulation (B4), readiness and intention to use (B5), and the current state of work (B6). The blocks correspond in turn to the technological, organisational and environmental sides of the TOE framework (Tornatzky & Fleischer, 1990; Baker, 2012), with intention and current state added. The trust block was broken down into general trust, perceived reliability and accuracy, willingness to rely on the tools, and concern about data security. Six open questions followed, on tasks suited to AI, fears, time losses, training needs and ideas for the respondent's own department. Reliability by block, measured with Cronbach's alpha, runs from 0.76 to 0.92, and the open

answers were coded thematically (Saldana, 2013). Participation was voluntary and anonymous, consent was implied by completing the questionnaire, and the answers were analysed only in aggregate, in line with the GDPR.

The interviews warrant fuller description. The ten roles span all five hierarchical levels of the company, from the general manager (strategic level), through tactical roles in engineering, production preparation, procurement, quality and production management, to operational staff, including a shop-floor line worker; roles held by several people were interviewed in parallel, which is how ten roles yield fifteen interviews. The interviews belong to the company's lean initiative: they were conducted in May 2026 for the lean rollout, not for AI specifically, and this study draws on them as qualitative evidence about the state of the processes. Participants were selected purposively so that every core process was represented. All interviews followed a common semi-structured guide covering the respondent's process, the wastes and bottlenecks encountered, current tool and documentation use, and expectations of the lean transformation. Transcripts were coded against a predefined lean framework, built from the five lean principles (Womack & Jones, 1996), the eight wastes (TIMWOODS) and a catalogue of fourteen lean tools, using a three-point presence scale (1 = explicitly mentioned; 0.5 = implicit or possible; 0 = not mentioned), and verbatim quotations of up to thirty words were retained for interpretive validity. The five recurring problems reported in Section 4 emerged from this coding; employee attitudes to AI were measured separately, by the survey described next.

The survey items likewise have a documented origin. The usefulness, ease-of-use and intention statements (B1, B5) were adapted from the technology-acceptance tradition (Davis, 1989; Venkatesh & Bala, 2008); the organisational and environmental statements (B3, B4) operationalise the TOE framework (Tornatzky & Fleischer, 1990; Baker, 2012); and the trust and data-security statements (B2) reflect the concerns documented for LLM adoption in construction (Ghimire et al., 2024; Ma et al., 2025). Item wording was reviewed with company management and refined through two internal iterations before distribution. In addition to descriptive statistics, block scores were formed as the mean of a respondent's items in each block, and the relationships among them were examined with Pearson correlations, an ordinary least squares regression on the intention block, and Kruskal-Wallis tests across levels of prior AI experience.

6 Preliminary implementation framework

6.1 Process-level AI use cases

Table 1 ties the company's processes and their documented problems to specific AI applications and the benefits each would bring. It combines the literature in Section 3 with the internal analysis in Section 4.

6.2 Departments, benefits and problems addressed

The first wave should take in the departments whose work is mostly about information: commercial and procurement, design and engineering, production preparation and technology, project management, accounting and quality management, with top management as the sponsor. The shop floor comes in only indirectly at this stage, through AI-generated visual work instructions and enlarged views of drawings, well before any direct automation. What the company stands to gain is time back on repetitive and administrative work, fewer reworks caused by documentation, less waiting once planning improves, quicker quotation, knowledge kept in a searchable base rather than in people's heads, and steadier quality. Each of these answers directly to one of the five problems set out in Section 4.

Table 1. Mapping of business processes to AI applications and expected benefits

Process	Documented problem	AI application	Expected benefit	Phase
Sales and quotation	Manual processing of inquiries	LLM-based extraction of requirements; draft offers	Faster, more consistent quotations	1
Design and engineering	Late or retroactive documentation; rework	Documentation completeness checks; generative and parametric design	Fewer reworks; faster design variants	1; 3
Production planning	No company-level plan; waiting	AI-supported scheduling extending the Last Planner System	Less waiting; higher plan reliability (PPC)	2
Procurement and warehouse	Manual and duplicate ordering	Reorder-point logic and duplicate detection over ERP data	Fewer stockouts and surpluses	1-2
Quality control	Manual inspection; no root-cause analysis	Machine-vision inspection; RAG-based defect diagnostics	Fewer defects and complaints	2; 1
Management and QM system	Administrative burden; audit preparation	RAG knowledge base over the quality manual and procedures	Lower administrative load; better compliance	0-1

6.3 Timing of adoption

Two arguments about timing follow from this. The first is that readiness is built by doing, through training, in-house capacity and partnerships (Ma et al., 2025; Sanchez et al., 2025), which argues for starting now with low-risk office and documentation tasks that do not hinge on the quality of production data. The second is that capital-heavy applications, such as robotics, automated guided vehicles and vision systems wired into the lines, assume stable processes and trustworthy data, and so belong after the lean work has settled and data interoperability has improved (Wang et al., 2025; Rangasamy & Yang, 2025). The path proposed here therefore begins at once with two phases. Phase 0 is governance: usage rules that satisfy the GDPR and the EU AI Act, an internal owner, and basic training. Phase 1 is an office AI assistant and a RAG knowledge base. Phase 2, a machine-vision pilot in quality control together with AI-supported planning, falls within six to

twelve months, and Phase 3, generative design and robotics de-risked with digital twins, sits one to two years out. Given the low regional adoption rate and export customers who expect ever more digital maturity, putting off the first phases would simply throw away a cheap chance to learn.

6.4 Internal ownership and the role of external consultants

On outside expertise, the evidence points to a hybrid arrangement. A shortage of skills is one of the most consistently reported barriers (Sanchez et al., 2025; Wang et al., 2025), and manufacturers of this size seldom have the in-house ability to build a RAG system or a machine-vision application. Bringing in specialists for those well-defined technical pilots, and for the first round of training, therefore makes sense. Ownership of the initiative is another matter, and it has to stay inside the company. The interviews showed the parallel lean effort losing momentum whenever no one

internal owned it, and the adoption literature is consistent that management engagement is what carries these projects (Bevilacqua et al., 2025). Handing AI adoption over wholesale would risk a poor fit with the processes and a lasting dependency. The model that fits is therefore an internal owner of the AI initiative, tied into the lean governance structure and backed by external consultants only for specified technical deliverables.

Set against existing roadmaps, the proposed phasing is consistent with the staged, value-chain sequencing advocated for modular construction (Pan et al., 2022) and with the phased SME roadmap of Sanchez et al. (2025), while differing in two respects: it adds an explicit governance phase before any pilot, and it ties the sequence to the company's lean transformation and to measured employee readiness rather than to technology maturity alone. For now it remains a proposal rather than a tested framework: it has not been implemented or benchmarked against alternatives, and its value can be confirmed only by the planned Phase 0-1 pilots and a follow-up readiness measurement.

7 Survey results and discussion

7.1 Sample and demographics

Sixty-three employees completed the survey, spread across every department. The largest groups were design and engineering (19) and commercial and procurement (14), followed by project management (8), production preparation and technology (7), quality control (7), production (5) and accounting (3). By role, constructors and technologists (20) and managers (17) were the most numerous, alongside clerical staff and other professions. The sample is even across age, with

most respondents between 30 and 49 (39), and tenure runs the full range, from under two years to more than twenty. These are people who live at a computer: 40 are at one all day, and another 18 for several hours. Experience with AI is already common. Sixteen use it regularly, 35 now and then, and only five never. Willingness to spend time learning is modest but real, with most prepared to give between half an hour and two hours a week, and only four unable to free up any time at all. Because participation required regular computer and e-mail use, the sample represents office and engineering staff rather than the shop floor, and the computer-use item reflects screen time during the working day, not shift length. What respondents mean by AI here is generative AI: the questionnaire introduced it with the examples of ChatGPT, Copilot and Claude, and these are also the tools they report using (Section 7.4).

7.2 Readiness across the TOE blocks

Table 2 gives the mean level of agreement and the reliability of each block. The strongest signal is intention. The readiness-and-intention block scores highest ($M = 5.32$), 86% of respondents sit above the midpoint, and the leading statements are the intention to use the tools ($M = 5.59$) and the willingness to try them ($M = 5.54$). Employees also see AI as something they can pick up, since the statement on ease of learning is the highest in the technology block ($M = 5.40$), even if they are more guarded about how far it will speed up their work or improve its quality ($M = 4.49$ and 4.35). Trust sits in the middle, at $M = 4.49$ across the positively worded statements. People are readier to lean on the tools ($M = 4.89$) than to credit them with consistent reliability ($M = 4.13$), and worry about the security and confidentiality of data is spread right across the scale ($M = 4.11$; $SD = 1.77$).

Table 2. Employee readiness by block (seven-point Likert scale)

Block	Content	Items	M (SD)	alpha
B1	Usefulness and ease of use (technology)	4	4.76 (1.23)	0.80
B2	Trust in AI (positively worded items)	4	4.49 (1.34)	0.92
B3	Organisational readiness	8	4.14 (1.09)	0.87
B4	Environment - market pressure	3	5.19 (1.11)	0.76
B5	Readiness and intention to use	4	5.32 (1.37)	0.92
B6	Current state (waiting; repetitive work)	2	4.95 (1.49)	-

Note. M = mean (1-7), SD = standard deviation, α = Cronbach's alpha. The data-security concern item (B2; $M = 4.11$) and the regulatory-knowledge item (B4; $M = 3.90$) are reported separately owing to their opposite direction and distinct content, respectively.

Table 3. Pearson correlations among the block scores

	B1	B2	B3	B4	B5	B6
B1 Usefulness and ease of use	1					
B2 Trust in AI	.82	1				
B3 Organisational readiness	.53	.47	1			
B4 Market pressure	.66	.64	.36	1		
B5 Intention to use	.74	.78	.48	.71	1	
B6 Current state	.41	.30	.14	.42	.44	1

Note. $N = 63$ ($B6: N = 62$, pairwise). Coefficients above .25 are significant at $p < .05$ and above .33 at $p < .01$. B2 comprises the positively worded trust statements; B4 the three market-pressure statements.

Pressure from outside is felt clearly enough. Respondents agree that customers and partners expect steadily more digitalisation ($M = 5.65$) and that AI would make the company more competitive ($M = 5.06$), but knowledge of the legal framework, the GDPR and the EU AI Act, trails behind ($M = 3.90$; $SD = 1.97$), which points to a real gap in regulatory literacy. The lowest scores belong to organisational readiness ($M = 4.14$). Inside that block, management support ($M = 5.47$) and the expectation of training ($M = 5.02$) are high, but a clear vision ($M = 3.89$), an open culture ($M = 3.61$), time to learn ($M = 3.32$) and the state of the data and IT base ($M = 3.02$) all fall below the midpoint. The current-state statements bear out the waiting problem from the interviews. Respondents agree strongly that they often wait for information or documentation ($M = 5.34$), and rather less that repetitive tasks eat their time ($M = 4.56$).

The same shape shows up throughout. At the level of the individual, readiness, openness and a sense that the tools are easy to use are all high, while the organisational footings of time, the data base, a clear vision and the culture lag behind. That is exactly the case for the order proposed in Section 6: begin with low-risk office and documentation work that does not depend on the quality of production data, put governance and training around it, and hold the more expensive applications until data and processes have been brought into shape. Strong management support sits next to a weak score for clarity of vision, and the combination says something specific, that the moment has come to write that vision down and say it out loud to the staff.

One caveat about scope follows from the instrument itself. Because the questionnaire introduced AI through generative-AI examples, the readiness and intention measured here concern generative-AI and LLM-based office tools, the technology of Phases 0 and 1, rather than the machine-vision and predictive-scheduling applications of Phases 2 and 3, which are a different technology class and will warrant their own readiness check before rollout. The alignment is deliberate: the framework begins exactly where measured readiness is highest.

7.3 Relationships among the constructs

Table 3 reports the correlations among the block scores. The intention to use AI (B5) is strongly associated with usefulness and ease of use ($r = .74$), trust ($r = .78$) and market pressure ($r = .71$; all $p < .001$), and moderately with organisational readiness ($r = .48$) and the current-state pressures of waiting and repetitive work ($r = .44$). Concern for data security is negatively related to trust ($r = -.49$, $p < .001$) and to intention ($r = -.32$, $p = .010$). Prior experience with AI goes hand in hand with usefulness ($r = .48$), trust ($r = .49$) and intention ($r = .40$; all $p \leq .001$), whereas age is unrelated to intention ($r = -.06$, n.s.): readiness is broadly distributed across age groups, not a property of the young.

A regression of intention on the four TOE blocks explains 70% of its variance ($R^2 = .70$, adjusted $R^2 = .68$, $F(4, 58) = 34.1$, $p < .001$). Only trust ($\beta = .42$, $p = .002$) and market pressure ($\beta = .31$, $p = .002$) are significant independent predictors; usefulness adds little once trust is controlled, reflecting how tightly the two are entwined ($r = .82$). Intention, usefulness and trust all differ significantly by prior AI experience (Kruskal-Wallis, all $p \leq .002$), while organisational readiness does not ($p = .13$), as expected, since it describes the company rather than the person. The pattern mirrors the wider evidence: experience-driven acceptance echoes the learning effects reported for generative-AI assistants (Brynjolfsson et al., 2025), and the primacy of trust matches the barriers reported for LLMs in construction (Ghimire et al., 2024; Ma et al., 2025). For the framework this means the first lever is trust, protected by governance, data-security rules and honest training, and the second is experience itself, which the low-risk Phase 1 pilots are designed to supply.

7.4 Qualitative findings

The open questions, answered by between 42 and 53 people, gave a concrete picture that lines up with the numbers (Table 4). Asked which tasks suit AI best, respondents named translation and foreign-language

correspondence, drafting and tidying up e-mails and letters, building material specifications by pulling data out of CAD and Revit models, searching technical data, standards and catalogues, and analysing prices and offers. These are almost exactly the information-heavy departments marked out for the first wave in Section 6.2, and the use cases in Table 1.

Fears are mild. About half of the respondents say outright that they have none. Among the rest, two worries dominate: whether the output is accurate and reliable, which they feel must always be checked, and the security and confidentiality of company data. A few warn about leaning on the tools too heavily and letting their own judgement slide, and a handful make the point that the company's systems and data have to be put in order before AI can do anything useful, which is the same thing the low score for data readiness was saying. On where time goes, the answers echo the interviews: documentation that is late or incomplete, waiting for materials and information, a poor flow of information, and stock figures in the system that do not

match the shelf. The training people ask for is hands-on, meaning short workshops built around real examples and tied to the tools they already use (CAD, Excel, Opera), help with writing prompts, and clear rules on what may and may not be typed into a tool. Their own suggestions most often describe a system that would join up the production plan, the state of the documentation and the availability of resources and raise a flag when something is missing, together with a searchable store of past projects and solutions. These are, in other words, the two things the framework already rests on, AI-supported planning and a RAG knowledge base. A good number already use these tools at work. ChatGPT comes up most often (32 mentions), then Claude (12) and Gemini (8), with the odd mention of Copilot, NotebookLM and Mistral, while eight respondents use none. That this is already happening, unmanaged, is one more reason to put usage rules and governance in place sooner rather than later.

Table 4. Thematic summary of the open-ended responses

Open-ended question	Most frequent themes
Tasks suited to AI	Translation and foreign-language correspondence; drafting and revising e-mails and letters; material specifications from CAD/Revit; searching standards and technical data; price and offer analysis
Fears and concerns	No fear (about half); accuracy and reliability of outputs; security and confidentiality of data; over-reliance and decline in critical judgement
Time losses	Late and incomplete documentation; waiting for materials and information; poor information flow; inaccurate stock levels
Training needed	Practical, example-driven workshops; integration with existing tools (CAD, Excel, Opera); prompt-writing instruction; data-protection rules
Application proposals	Linking the production plan, documentation status and resources with alerts; a searchable knowledge base from the project archive
Tools in use	ChatGPT (32), Claude (12), Gemini (8); isolated Copilot, NotebookLM, Mistral; 8 respondents use none

7.5 Limitations and future work

The limits of the study follow from its design: a single case, self-reported answers, and a single point in time at one company. Any generalisation beyond comparable manufacturing mid-caps therefore needs care. Anonymity, useful as it is, also meant that non-response could not be examined below the level of the department, and the sample is too small to break down reliably into subgroups. A few of the review articles the synthesis leans on were available only as abstracts. Because the evidence comes from one organisation, the findings generalise analytically rather than statistically (Yin, 2018): they transfer most readily to manufacturing mid-caps of comparable size, export orientation and lean maturity. The correlational and regression results rest on 63 respondents and should be read as exploratory; the production subgroup in particular is too small to support departmental conclusions. The next steps are to put Phase 0 and

Phase 1 into practice and then to measure readiness again after the first pilots, which would move the framework from a preliminary proposal to something tested against evidence.

8 Conclusion

This paper set recent work on AI in modular construction and on AI adoption in manufacturing SMEs against the documented process problems of one Croatian mid-cap manufacturer of modular buildings. The reading of the evidence is threefold. The nearest gains lie not in expensive automation but in office, documentation and quality work. Adoption should move in phases kept in step with the company's lean transformation, starting straight away with governance and a few low-risk pilots. And the most realistic way to govern it is a hybrid one, with internal ownership and outside expertise brought in only where it is

genuinely needed. Within the limits of a single case study, the survey backs this up. Employees are willing and open, but they rate the organisational footings, time, the data base, a clear vision and the culture, as the weakest link, and that is precisely what gives the governance framework, the training and the modest first pilots their justification. The regression points the same way: trust and perceived market pressure are the main levers of intention, so the immediate task is to protect trust through governance, data-security rules and honest communication about what the tools can and cannot do, while hands-on experience builds the rest.

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