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# Artificial Intelligence, BIM, and Circular Economy in Construction: Economic Implications and Industry Adoption

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**Abstract.** The integration of Artificial Intelligence (AI) and Building Information Modelling (BIM) within the circular economy framework represents a transformative shift in construction industry practices and economic performance. This paper investigates the perception, adoption levels, and economic implications of AI and BIM implementation in the construction sector, with a focus on circular economy principles. The research is grounded in empirical data collected through two questionnaire surveys conducted in 2024 and 2025 targeting construction professionals in Slovakia. The surveys assessed AI utilization levels, digital competencies, perceptions of AI impact across construction lifecycle phases, and the economic importance of AI-supported processes. Results indicate that AI utilization levels remain relatively low but show a positive trend between the survey periods (mean 2.03/5 in 2024 vs. 2.31/5 in 2025). In 2024, the highest AI impact expectations were identified for the facility management phase (mean 3.82/5), cost management (mean 3.67/5), and schedule optimization (mean 3.61/5). The 2025 survey revealed that cost monitoring, schedule planning, and client satisfaction are the most critically valued performance indicators (means above 4.1/5), while AI training levels among professionals remain low (mean 1.83/5). The findings highlight a persistent gap between the recognized potential of AI and BIM and their actual adoption, particularly in circular economy-related areas such as waste management and materials optimization. The study underscores the need for targeted training initiatives and strategic frameworks to accelerate AI and BIM integration in support of circular construction economics.

**Keywords:** Artificial intelligence; construction management; organizational barriers; firm size; technology adoption; digital transformation

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## INTRODUCTION

Artificial intelligence (AI) has gradually moved from experimental applications towards practically usable tools across the construction life-cycle, including design optimization, cost and schedule forecasting, risk assessment and site safety monitoring [1, 2]. Scientometric evidence documents a rapid growth of research activity on AI in architecture, engineering and construction over the past decade [3]. At the same time, the gap between the demonstrated potential of AI and its routine use in construction companies remains considerable.

Systematic reviews of AI adoption in construction consistently report that obstacles are not limited to algorithms and computing infrastructure: they span data availability, financing, skills and, importantly, the organization itself [4]. The construction industry has digitalized more slowly than most other sectors, and structural and organizational characteristics of construction companies are repeatedly identified among the reasons [5]. Research on Construction

4.0 shows that the industry's transformation depends on the interplay of technologies such as building information modelling (BIM), automation and data analytics with the organizational environment into which they are introduced [6]. A systematic review of technology implementation in construction likewise concludes that organizational factors, including management support and organizational readiness, recur as critical determinants of implementation success [7].

The broader information systems literature emphasizes that the value of AI depends on complementary organizational change rather than on technology acquisition alone [8]. For construction companies specifically, acceptance of AI-based technologies has been shown to be shaped by the organizational context in combination with the perceived characteristics of the technology [9]. Nevertheless, quantitative empirical studies that isolate the organizational dimension of AI adoption and compare its perception across firm-size categories are scarce, particularly for Central European construction markets.

The study aims to identify the most important organizational barriers to artificial intelligence implementation in construction firms and to examine whether their perceived severity differs according to firm size. Two research questions are addressed. RQ1: Which organizational barriers are perceived as the most important obstacles to AI implementation in construction firms? RQ2: Does the perceived severity of organizational barriers differ according to construction firm size? One non-directional hypothesis is tested. H1: The perceived severity of organizational barriers to AI implementation differs significantly among micro, small, medium-sized and large construction firms. The remainder of the paper presents the theoretical background, the data and methods of the exploratory questionnaire study, the results of the descriptive and inferential analysis, and a discussion of the findings, their practical implications and limitations.

# THEORETICAL BACKGROUND

## Organizational Readiness for AI

Organizational readiness for change denotes the extent to which organizational members are collectively willing and able to implement a change, and it is considered a precondition for successful implementation of new practices [10]. Applied to AI, readiness involves a specific configuration of factors: a clear strategic orientation towards AI, commitment of top management, availability of resources and knowledge, and a culture that tolerates experimentation [11]. Studies of AI business value converge on the conclusion that adoption is a socio-technical transformation, in which value is realized only when technological resources are combined with organizational capabilities and adjusted processes [12, 13]. From this perspective, organizational barriers are not residual “soft” factors but central determinants of whether AI initiatives progress beyond isolated pilots.

## Organizational Barriers to AI Adoption in Construction

Reviews of AI in construction identify a family of organizational obstacles: reluctance of established organizations to change working procedures, conservative industry culture, unclear responsibility for AI initiatives and limited managerial commitment [2, 4]. Evidence on technology implementation in construction more broadly confirms that management support, organizational structure and process maturity condition implementation outcomes [7]. Firm-level studies show that organizational context variables complement technology-related perceptions in explaining construction companies' intention to use AI-based technologies [9]. Drawing on this literature, the present study concentrates on seven organizational barriers that can be grouped into three areas: behavioral-cultural barriers (resistance to change, conservative organizational culture, hierarchical management with low innovation flexibility), strategic-leadership barriers (absence of a clear AI strategy, weak top-management support for digitalization) and process-operational barriers (low process standardization, difficulty in transferring innovations from experiments and pilots to routine project management).

## Firm Size and Digital Transformation

Classical innovation-adoption theory treats organizational attributes as determinants of the rate and success of adoption [14]. The technology–organization–environment framework explicitly places organizational size and structure among the factors shaping technology adoption decisions [15], and models of technology acceptance stress facilitating organizational conditions [16]. The dynamic-capabilities perspective adds that organizations differ in their capacity to sense opportunities, reconfigure processes and routinize new technologies [17]. Empirical evidence on the relationship between organizational size and innovation indicates that size is positively associated with the adoption

of innovations, but also that larger organizations face greater structural complexity and coordination costs [18]. In the European context, firm-size categories are conventionally defined by headcount thresholds for micro, small, medium-sized and large enterprises [19]. For smaller companies, limited resources and expertise constrain the adoption of AI, whereas their shorter decision paths may make organizational obstacles less salient; surveys of AI in small and medium-sized enterprises document both the resource constraints and the relative flexibility of smaller firms [20]. How these opposing tendencies balance out in construction companies' perception of organizational barriers to AI is an open empirical question.

### Relevance to Digital Construction and Sustainability

The organizational capacity of construction companies to adopt AI has consequences beyond the technology itself. Construction generates large volumes of project data whose exploitation for decision-making depends on adequate analytical capability [21], and machine learning is increasingly coupled with BIM across the building lifecycle [22]. Reviews of digitalization and automation across the construction project life cycle show that digital technologies increasingly support planning, monitoring and control [23], and decision-support methods are an established stream of construction management research [24, 25]. Effective inter-organizational cooperation has likewise long been recognized as a condition of construction project performance [26]. The examination of organizational barriers to AI adoption therefore complements the project's wider research context of digitalization, decarbonization and circular construction, while the specific objective of identifying and comparing organizational barriers by firm size is the contribution of this paper.

## MATERIALS AND METHODS

### Research Design

The study is designed as an exploratory, cross-sectional questionnaire study of construction professionals. It draws on a broader questionnaire survey on barriers and challenges of AI implementation in construction, which covered data-related, technical, human-capital, financial, organizational and ethical-legal barrier areas; only the organizational module and firm characteristics are analyzed in this paper, and results for the other barrier areas are not reported here. The questionnaire was administered online; the responses analyzed in this study were collected. Respondents were professionals working in construction companies operating in Slovakia. The sampling procedure was non-probabilistic and the response rate could not be determined Participation was voluntary and anonymous; no personal identifying data were collected Given the sampling approach and sample size, the study is presented as a pilot empirical study and no claim of representativeness for the construction industry is made.

### Sample Characteristics and Measurement

The analysed dataset contains 55 valid responses with no missing values in the analysed variables and no duplicate records. Firm size was measured by the number of employees using the conventional European classification of micro (up to 9 employees), small (10–49), medium-sized (50–249) and large (250 and more) enterprises [19]. The sample comprises 6 micro, 9 small, 17 medium-sized and 21 large companies. Table 1 summarizes the main characteristics of the research sample.

Seven organizational barriers to AI implementation were each rated on a five-point Likert-type scale (1 = very weak influence, 5 = very strong influence on AI implementation), so that a higher value indicates a higher perceived severity of the barrier: (i) resistance to change in the organization; (ii) conservative organizational culture; (iii) hierarchical management and low flexibility for innovation; (iv) absence of a clear AI strategy; (v) weak support of digitalization by top management; (vi) low standardization of processes; and (vii) difficulty in transferring innovations from experiments and pilot solutions to routine project management. A composite Organizational Barrier Index (OBI) was computed as the arithmetic mean of the seven items for respondents with at least six valid item responses (in this dataset, all respondents answered all seven items). Internal consistency of the scale was assessed with Cronbach's alpha [27], corrected item-total correlations and alpha-if-item-deleted values.

### Statistical Analysis

Descriptive statistics (mean, standard deviation, median, quartiles, share of ratings 4–5) were computed for each item and for the OBI. Because the grouping variable has four categories with unequal and partly small group sizes and

the response scale is ordinal, the main comparison of the OBI among firm-size groups used the non-parametric Kruskal–Wallis H test [28]; the distribution of the OBI was additionally inspected with a histogram, a Q–Q plot and the Shapiro–Wilk test as supplementary information. The effect size for the Kruskal–Wallis test was quantified as epsilon-squared, computed as $\varepsilon^2 = H/(n - 1)$, where H is the test statistic and n the total sample size [29]. In the case of a significant omnibus test, pairwise Dunn tests [30] with the Holm correction for multiple comparisons [31] were applied. Item-level Kruskal–Wallis tests for the seven individual barriers were conducted only as an exploratory supplementary analysis with Holm correction across the seven tests, and the Spearman rank correlation between ordinally coded firm size and the OBI was computed as supplementary information. The significance level was set at $\alpha = 0.05$. All computations were performed in Python 3 (pandas, SciPy, scikit-posthocs) with a fully reproducible analysis script; all reported numbers originate from this script.

# RESULTS

## Characteristics of the Sample

Table 1 presents the structure of the research sample. Respondents most often represented companies focused on the realization of construction works (43 of 53), with international (21) or regional (17) territorial scope. The self-assessed level of company digitalization was predominantly medium (27 of 53). Regarding current AI use, 17 companies planned but had not yet started using AI, 13 used AI occasionally, 11 were piloting AI solutions, 8 did not plan AI use and 4 used AI regularly.

**TABLE 1.** Characteristics of the research sample (n = 53).

| Characteristic | Category | n | % |
|---|---|---|---|
| Firm size (employees) | Micro (up to 9) | 6 | 11.3 |
| | Small (10–49) | 9 | 17.0 |
| | Medium-sized (50–249) | 17 | 32.1 |
| | Large (250 and more) | 21 | 39.6 |
| Main business focus | Realization of construction works | 43 | 81.1 |
| | Design activities | 4 | 7.5 |
| | Other (production, development, consulting) | 6 | 11.3 |
| Territorial scope | International | 21 | 39.6 |
| | Regional | 17 | 32.1 |
| | National | 13 | 24.5 |
| | Local | 2 | 3.8 |
| Digitalization level (self-assessed) | High / rather high | 12 | 22.6 |
| | Medium | 27 | 50.9 |
| | Rather low / low | 14 | 26.4 |
| Current AI use | Regularly | 4 | 7.5 |
| | Occasionally | 13 | 24.5 |
| | Testing / piloting | 11 | 20.8 |
| | Not yet, but planned | 17 | 32.1 |
| | Not used and not planned | 8 | 15.1 |

## Perceived Organizational Barriers

Table 2 reports the descriptive statistics of the seven organizational barriers, ordered by mean severity. The absence of a clear AI strategy was rated as the most severe organizational barrier (mean 3.42, SD 1.18), with more than half

of the respondents (50.9%) assigning a rating of 4 or 5. It was followed by weak top-management support for digitalization (mean 3.40, SD 1.08) and low standardization of processes (mean 3.32, SD 1.00). Resistance to change in the organization received the lowest mean rating (3.13, SD 1.14), although even for this item more than one third of respondents chose a rating of 4 or 5. The narrow range of means (3.13–3.42 on the five-point scale) indicates that respondents perceived all seven organizational barriers as moderately to considerably important.

**TABLE 2.** Descriptive statistics for organizational barriers to AI implementation (n = 53), ordered by mean.

| Organizational barrier | Mean | SD | IQR | Ratings 4–5 (%) |
|---|---|---|---|---|
| Absence of a clear AI strategy | 3.42 | 1.18 | 1 | 50.9 |
| Weak top-management support for digitalization | 3.40 | 1.08 | 1 | 43.4 |
| Low standardization of processes | 3.32 | 1.00 | 1 | 47.2 |
| Conservative organizational culture | 3.30 | 1.23 | 2 | 41.5 |
| Hierarchical management and low innovation flexibility | 3.28 | 1.13 | 1 | 41.5 |
| Difficulty transferring pilots to routine management | 3.28 | 1.06 | 1 | 45.3 |
| Resistance to change in the organization | 3.13 | 1.14 | 2 | 35.8 |

## Reliability of the Organizational Barrier Scale

The seven-item scale showed excellent internal consistency (Cronbach's alpha = 0.934). Corrected item-total correlations ranged from 0.73 to 0.82 and the alpha-if-item-deleted values (0.921–0.929) did not indicate that removing any item would improve reliability; all items were therefore retained also on content grounds, since each represents a conceptually distinct organizational obstacle. The composite OBI had a mean of 3.30 (SD 0.95, median 3.29) and its distribution showed no extreme outliers (Shapiro–Wilk $W = 0.975$, $p = 0.326$, reported as supplementary information only).

## Differences According to Firm Size

Table 3 and Figure 1 summarize the OBI by firm size. The mean perceived severity of organizational barriers increased monotonically from micro companies (mean 2.57, SD 0.86) through small (3.08, SD 0.61) and medium-sized companies (3.19, SD 1.06) to large companies (3.70, SD 0.87). The Kruskal–Wallis test indicated a statistically significant difference among the four groups ($H(3) = 10.085$, $p = 0.018$), with an effect size of $\varepsilon^2 = 10.085/52 = 0.194$, i.e. approximately 19% of the variability in ranked OBI scores was associated with firm size. Hypothesis H1 was therefore supported. Dunn post hoc tests with the Holm correction identified one significant pairwise difference, between micro and large companies (adjusted $p = 0.030$); the remaining pairwise comparisons were not significant after correction (adjusted $p \geq 0.175$). The supplementary Spearman correlation between ordinally coded firm size and the OBI was $\rho = 0.436$ ($p = 0.001$), consistent with the monotonic pattern. Exploratory item-level Kruskal–Wallis tests showed unadjusted p-values below 0.05 for conservative organizational culture, hierarchical management and low process standardization, but none of the seven item-level tests remained significant after the Holm correction (adjusted $p \geq 0.192$); the item-level pattern is therefore reported only as a descriptive tendency mirroring the composite result.

**TABLE 3.** Organizational Barrier Index according to firm size and the Kruskal–Wallis test result.

| Firm size | n | Mean | SD | Median | Q1 | Q3 |
|---|---|---|---|---|---|---|
| Micro | 6 | 2.57 | 0.86 | 2.14 | 2.00 | 2.82 |
| Small | 9 | 3.08 | 0.61 | 3.00 | 2.86 | 3.14 |
| Medium-sized | 17 | 3.19 | 1.06 | 3.29 | 2.57 | 3.71 |
| Large | 21 | 3.70 | 0.87 | 3.86 | 3.14 | 4.29 |
| Kruskal–Wallis: $H(3) = 10.085$, $p = 0.018$, $\varepsilon^2 = 0.194$ | | | | | | |

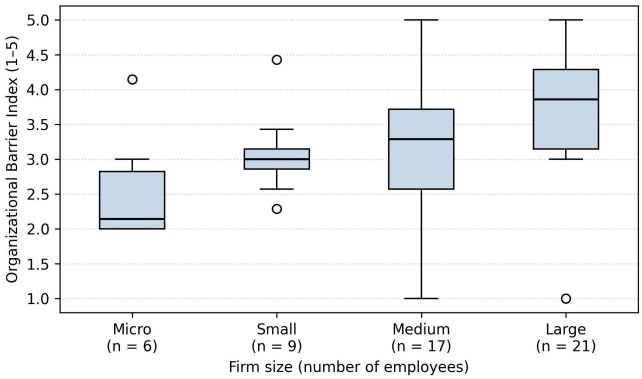


**FIGURE 1.** Boxplot of the Organizational Barrier Index (mean of seven items, scale 1–5) according to firm size.

## DISCUSSION

With respect to RQ1, the analysed sample indicates that strategic-leadership barriers dominate the organizational dimension of AI adoption: the absence of a clear AI strategy and weak top-management support for digitalization received the highest severity ratings, followed closely by low process standardization. This ordering is consistent with the organizational AI-readiness literature, which places strategic orientation and management commitment among the primary readiness factors [11, 12], and with review evidence from construction showing that management support conditions technology implementation outcomes [4, 7]. Notably, resistance to change, often assumed to be the archetypal obstacle in a conservative industry, was rated lowest of the seven barriers, although still at a moderate level. The results suggest that, in the perception of the respondents, the bottleneck lies less in the workforce's unwillingness and more in the absence of strategic direction and standardized processes into which AI could be embedded.

With respect to RQ2, differences were identified: the perceived severity of organizational barriers increased with firm size, the omnibus test was significant with a relatively large effect size, and the contrast between micro and large companies remained significant after correction. Several non-exclusive explanations are plausible and supported by the organizational literature. Larger organizations have more complex structures, more management levels and more fragmented processes, which raises coordination costs of any cross-cutting innovation [18]. Innovation approval tends to be more formalized, and pilot solutions must be scaled across departments, projects and often legacy information systems, which is precisely where AI initiatives frequently stall [11, 12]. Respondents from larger companies may also simply be more aware of organizational shortcomings, having observed the distance between corporate digitalization strategies and everyday project practice. Conversely, in micro companies with short decision paths, the owner-manager can adopt or reject a tool directly, so organizational obstacles may genuinely be smaller or may be less visible because AI exposure is limited [20]. The observed pattern may therefore reflect a combination of real structural complexity and greater awareness of it; the present data cannot distinguish between these mechanisms, and no causal claim is made.

The findings have practical implications. For large construction companies, the results point to the need for an explicit AI strategy with visible top-management sponsorship, for process standardization as a precondition of scaling, and for governance mechanisms that manage the transfer of successful pilots into routine project management. For small and micro companies, the comparatively lower perceived organizational barriers suggest that, once resource and skill constraints are addressed, organizational absorption of AI tools may be less problematic; support programmed could therefore concentrate on access to expertise and affordable solutions rather than on organizational restructuring. For industry associations and policymakers, the size gradient implies that uniform, one-size-fits-all digitalization support may miss the differing nature of the obstacles across the firm-size spectrum.

The results are also relevant to the broader research context of digital and sustainable construction. The usability of BIM- and AI-generated data for performance assessment, sustainability evaluation and circular-construction decision-making presupposes that companies are organizationally able to institutionalize digital tools in routine processes [21, 22, 23].

Several limitations must be acknowledged. The sample is small and non-representative, the firm-size groups are unequal (with only six micro companies), and the study is cross-sectional, so no causal inferences about firm size and barrier severity can be drawn. All measures are self-reported perceptions collected with a single instrument, which creates a risk of common method bias [32]; the anonymity of responses partially mitigates but does not remove this

risk. The data come from a single country context, which limits transferability. Finally, the study is exploratory: the composite index aggregates conceptually distinct barriers, and the item-level differences did not survive correction for multiple testing. Future research should replicate the comparison on larger stratified samples, ideally longitudinally, combine perceptions with objective adoption indicators, and examine the mechanisms (structural complexity, awareness, pilot-scaling governance) suggested here as possible explanations.

## CONCLUSION

This exploratory questionnaire study examined seven organizational barriers to AI implementation in construction companies and compared their perceived severity across firm-size categories on a sample of 53 professionals. Three findings stand out. First, respondents perceived strategic-leadership deficits, namely the absence of a clear AI strategy and weak top-management support for digitalization, together with low process standardization, as the most severe organizational barriers, while classic resistance to change ranked lowest. Second, the seven-item organizational barrier scale showed excellent internal consistency (Cronbach's alpha = 0.934), supporting the use of a composite Organizational Barrier Index in further research. Third, the perceived severity of organizational barriers differed significantly according to firm size ($H(3) = 10.085$, $p = 0.018$, $\varepsilon^2 = 0.194$), increasing monotonically from micro to large companies, with a significant post hoc contrast between micro and large firms. The analyzed sample indicates that organizational readiness for AI is size-dependent, and that support measures for AI adoption in construction should be differentiated accordingly: strategy, leadership commitment and pilot-scaling governance in larger companies, and access to expertise and affordable solutions in smaller ones. Given the exploratory design, the small non-representative sample and the single-country context, the findings should be interpreted cautiously and validated on larger samples. Within the wider research agenda of digitalization, decarbonization and circular construction, the results underline that the practical benefit of BIM, AI and related digital technologies depends on the organizational capacity of construction companies to turn pilots into routine practice.

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