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Citation for the original published paper (version of record):

Cusumano, L., Saraiva, R., Rempling, R. et al (2022). Intelligent building contract tendering - potential and exploration. IABSE Symposium Prague, 2022: Challenges for Existing and Oncoming Structures - Report: 1902-1909

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Intelligent building contract tendering – potential and exploration

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Abstract

Project tendering is the construction business "Tightrope-walking." It is a time-limited balance act where technical and business specialists find the best technical proposal at the right price. The purpose and aim of this study were to explore artificial intelligence (AI) in the tender work and to identify challenges and possibilities with data-driven decision-making. An AI work support tool was adopted and used to extract and process client requirements. The tool and digital-work procedure were presented and discussed with tender specialists from a large contractor in a workshop. A two-step survey was performed in connection to the workshop, investigating the potential users' insights and attitudes for implementation. The main result and conclusion were that AI and digitalization could support tendering; however, successfully generating business value will require higher levels of digitalization, well-structured databases, and access to historical project data.

Keywords: Digitalization; artificial intelligence; tender phase; data-driven decisions; production data; client requirements; text extraction.

1 Introduction

The construction industry is facing the challenge of reducing its emissions of greenhouse gases since the building sector globally is contributing 30% of the total greenhouse gas emissions [1]. Therefore, in several countries, Life Cycle Analysis requirements are introduced to visualize project-specific emissions and create awareness around the climate issue [2], which escalates the need for data collection and digitalization.

In such an early stage of a construction project as the tender phase, essential decisions such as structural and building service systems are made, decisions that significantly impact production and maintenance costs, greenhouse gas emissions, as well as construction time [3].

As stated by Galbraith [4], "A basic proposition is that the greater the uncertainty of the task, the greater the amount of information that has to be processed between decision makers during the execution of the task," which applies to tender project where various discipline specialists must cooperate to create competitive technical solutions. Important project and client-specific parameters must be analyzed, and factors like project risks, workload capacity, and chances for winning the bidding shall be considered. The information available for doing this work is the collected knowledge of the individuals in the tendering team.

A recent study by Jovanova and Saraiva explored tendering interrelations and advantages associated with reducing time employed during the elaboration of contractors' bids [5]. Traditionally, the work performed in the tendering phase consists of a lot of manual and time-consuming tasks. Hence, implementing more data-driven processes and AI might improve the work methods in the tendering process, creating opportunities for knowledge transfer from past projects. This can increase continuous improvement and encourage the adoption of more buildable solutions.

A growing number of researchers have been investigating opportunities to deploy technology to automate tasks in early project stages, such as window and door identification from pdf blueprints by convolutional neural network [6]; object detection in pictures of building facades [7]; and classification of room categories by image recognition and generative adversarial network on architectural drawings [8].

Even though image recognition has proven to have great potential, most information is text-based. This fact calls for research on the potential in text extraction and data processing of written client requirements.

2 Purpose and aim

The purpose of this study was to explore how digitalization and AI can enable data-informed decisions in early project phases.

The aim was first to adopt a proprietary tender phase AI tool prototype and then use it as a reference to assess how technical specialists from diverse disciplines involved in tender projects perceive the potential of the AI tool as support in their work.

3 Method

This study is designed as a case study, divided into the following steps:

- Initial study and adoption of a proprietary tender phase AI tool prototype
- A pre-workshop survey assessing the participants' optimism towards the suggested tool concept
- A workshop in which participants watched a demonstration of the tool prototype and brainstormed their impressions
- A post-workshop survey, akin to the first, assessing the participants' optimism after the workshop
- Data analysis, discussion, and conclusion

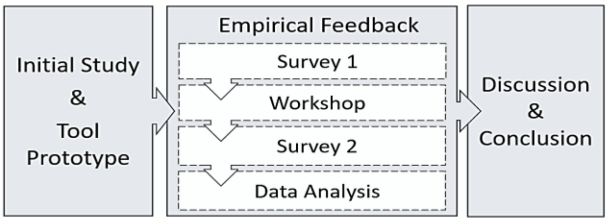

Figure 1. Method

As seen in Figure 1, the initial study for identifying the tool requirements and the development of the AI tool served as a base for collecting empirical data from the workshop and surveys.

This study has a contractor focus, and therefore only project procurements with design-build contracts, where the contractor can influence the design, have been studied.

3.1 Description of AI tool

The tool was developed to extract text from a frequently appearing tender document type: the technical building description. Figure 2 shows where in the tender process it is supposed to be used. Since most Swedish technical building descriptions follow the standard AMA-HUS, which facilitates material and performance requirements [9], the tool was programmed to identify and extract texts following AMA-HUS 18, further referred to as AMA.

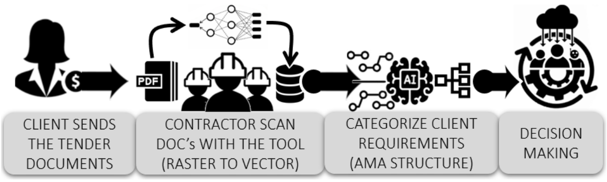

Figure 2. Tool dataflow concept

The tool code was programmed in Phyton with a web-based user interface in three modules:

- Import of new technical building descriptions
- Comparison between documents in the database
- Visualization of data from database

The tool uses natural language processing, transforming text into numeric vectors. First, technical building descriptions from ten different tender projects were imported to serve as an initial database. Then, data from the extracted text was automatically uploaded to a web-based dashboard.

3.2 Selection of participants

In Table 1, the invited technical disciplines are presented. Since the AI tool was developed for use within a specific contractor company, workshop participants were selected from personnel currently employed in that company.

The AI tool was developed for tender projects, and therefore, only employees frequently working in the tender phase were selected. Furthermore, since the workshop was digital, participants from all parts of Sweden could be invited.

The participation rate at the workshop (of those invited) can be seen in Table 1 below.

Table 1. The participation rate at the workshop

Specialist category	Participation rate [%]
Geo-technicians	27
Structural engineers	39
Energy/LCA/Sustainability engineers	43
Building service engineers	34
Cost estimators	47

3.3 Pre- and post-workshop survey

The participants were introduced to the topic of the study by being invited to answer a survey before the workshop individually. They also received information about the workshop structure and tools to be used by email.

The online self-completed survey was framed in three parts. The first addressed background questions (i.e., experience, specialization area, department, and geographic location). The second, comprised of four multiple-choice questions, assessed the respondents' optimism and preferences towards potential core features of the AI tool. Those were:

1. The value of automating the extraction of texts from tender documents PDF's and categorizing the collected data into some sort of structure
2. Preferred metadata structure
3. The usefulness of comparing project data to other projects in a database
4. Implementation viability, considering todays' tender processes dynamics

On questions 1, 3, and 4, the predefined response options and corresponding weights can be seen in Table 2.

Table 2. Closed-answers weights.

Answer	Weights
Totally agree / Very helpful	5
Partially agree / Useful	4

Neither	3
Partially disagree / Not so useful	2
Totally disagree / Not at all useful	1

The third and last part of the survey consisted of four open-answer questions in which the respondents were asked for insights regarding challenges, what needs to be done to overcome the challenges, opportunities, and desired future features.

The first survey was sent out by email to the 59 specialists who had previously accepted the workshop invitation. Of those, 38 (64%) answered it. The second survey was sent out by the end of the workshop, with 25 participants fully responding. When examining the changed level of optimism, only responses from specialists participating in all three steps (survey 1, workshop, and survey 2) were included, which resulted in 22 answers.

3.4 Workshop

Inspired by Jungk and Müllert's concept of Future Workshops [10] and Bosch-Sijtsema et al. methodology [11], the workshop was set to collect potential users' insights for further development of the AI tool. Partakers were hence encouraged and given ample freedom to brainstorm and propose out-of-the-box ideas.

The first part of the workshop was launched with the facilitator playing a video demonstration of the tool prototype. Participants were then divided into groups of 5-6 members of similar discipline-specializations (according to knowledge areas listed in Table 1) and invited to collaborate in Miro-boards [12].

Then, the facilitator encouraged groups to discuss their impressions of the tool and register emerging insights in post-it notes (facilitating data collection afterward). Group discussions were recorded to gather quantitative data and to address possible vagueness. After 40 minutes of unframed brainstorming, the participants were introduced to four categories:

- Challenges
- Opportunities
- Future Features
- What would need to be realized to achieve these opportunities

Additional 15 minutes were then given for groups to cluster their post-it notes under the perceived best-fit categories and add more insights.

Before the meeting ended, all participants were requested to answer another survey with the same questions as the first. The responses on the second survey were then compared with the first survey. The differences were later used to analyze if and how the tool presentation and workshop discussions influenced participants' optimism towards the tool.

4 Results

The result is presented in two parts. First, data collected from the survey reveals participants' level of optimism towards the tool. Then, in the second part, the result from the workshop is presented.

4.1 Survey Analysis

As previously described, the first part of the survey assessed respondents' backgrounds. One relevant finding showed that more than 70% have been working for ten years or more. Their answers to the question: "How many tendering projects have you been involved in during the last three years?" showed that 63% had worked with 13 or more tender projects.

Three survey questions measured respondents' level of optimism and preferences towards potential core features of the AI tool. Based on that system of weights, Table 3 presents the results from those closed-answer questions.

Table 3. Level of optimism

Topic	Survey 1 [%]	Survey 2 [%]
Usefulness of text extraction	85	79
Benchmarking opportunities	82	86
Ease of implementation	73	75

Question 2 asked respondents into which structure they preferred the extracted texts (from tender documents) to be categorized, and the answers are presented in Table 4.

Table 4. Preferred text structure

Text extraction structure	Survey 1 [%]	Survey 2 [%]
AMA	14	18
Structural parts	32	23
Other	9	23
I do not know	45	36

Only 14% of the participants in the first survey found the AMA structure helpful. In the second survey, it had slightly increased to 18%. 32% (in the second survey, 23%) preferred the information structured according to which structural/building part they belong to. The participants that answered "other" were also suggesting which other structure they preferred. Some of the answers were time plan activities and subject areas for energy, sustainability, or moisture. The biggest answer category was "I do not know."

4.2 Workshop Analysis

Following the method presented in subchapter 3.4, workshop participants contributed with several insights during their group discussions. After the meeting ended, the authors further interpreted the post-its and clustered them according to their meanings in identified sub-categories. Figure 3 introduces the 15 of them, along with their share in relation to their belonging categories.

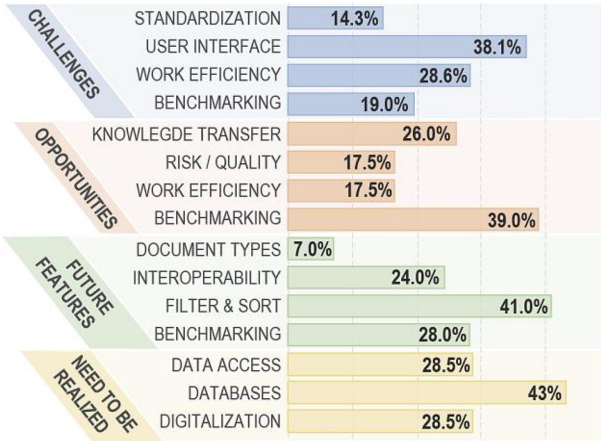

Figure 3. Workshop results

In the category "Challenges," 14.3% of the listed challenges regard the lack of standardization and how to use the tool if the document does not follow the assumed standard. 38.1% are related to the user interface and the complexity of using the tool appropriately. 28.6% of the issues questioned how the demonstrated tool could lead to better work efficiency and concerns where the tool should be used in the tender process. The remaining 19% mentioned the complexity of using it as a benchmarking tool, how the bigger picture might get lost, and how important non-written information might get lost.

As "Opportunity," 26% of the collaborator's inputs reflected the tool's potential to transfer knowledge from previous projects, which, in turn, helps to find simpler and cheaper technical solutions. 17.5% were related to risk minimization and the possibility of getting inputs from previously finished projects. Opportunities regarding work efficiency in large tendering projects accounted for 17.5% of the comments. However, the largest sub-category within opportunities was benchmarking, comprising 39% of the notes in this category. Many participants perceived the benefits of comparing new projects with previous ones based on categorizing parameters. For instance, some specialists mentioned the possibility of benchmarking warranty contractual conditions inter-projects, while others suggested that the tool could help keep track of problematic technical solutions in perspective to aftermarket performance.

In the category "Future Features," most comments (41%) were perceived as suggestions for filtering and sorting information considering varied parameters. For instance, many participants referred to filtering out projects with similar customer requirements and the same structural system given an extensive database of finished projects. Others brought up the possibility of highlighting high-risk products and technical solutions based on previous experience. A few noted that sending essential cost-driven requirements into a predefined template might be helpful in new tender projects. "Benchmarking" stood for 28% of the responses and mainly concerned functions like hit rates on similar projects and finding target prices for similar projects. Finally, 24% regarded the integration and communication of the introduced AI tool with solutions and software's currently in use in the organization.

In the fourth and last category, participants contributed with "what would need to be realized to achieve the desired opportunities." Although the less insightful category, with only a few notes added, a few crucial concerns were introduced, such as digitizing data from historical projects, creating databases, and allowing proper access. Another concern was the need to establish correct, relevant, and comparable information.

5 Discussions

The results from both the survey and workshop show an overall high optimism towards AI-supported tools in early project stages. There is a general belief that such a tool can help compare new projects to previous projects regarding requirement similarity, key numbers, and technical solutions. Making these comparisons in the tender stage can help minimize risks, detect potential mistakes in customer requirements, estimate costs, and identify best-fit technical solutions.,

AI tools can also help evaluate tendering offers, both within the contractor companies before presenting the offer to the client and to help clients assess incoming tender offers. To make any AI tool add value to the organization, there is a need to set up accessible databases. Some identified challenges in this study are how to add historical project data to new databases and how to make the data understandable and comparable. Connected to this is the general need for knowledge in digital technologies within the company and organizational agility, as found in the study of Brock and Wagenheim [13]. In both the workshop and surveys, the participants identified increased knowledge and new workflows as two factors that must be addressed.

As found in the workshop, standardization of both requirements and output is beneficial to increase the possibilities with text comparison. Today clients have various ways of specifying requirements, and contractors might lack standardized ways of presenting their tender offers in terms of key numbers, chosen technical solutions, and production methods connected to their offer. Working and production methods might also vary with geographical location. Those factors make collecting, comparing, and quality control data generated in the tendering stage challenging. If this data later shall be compared to production data, additional complexity is added since organizations might lack clear working and accounting method standards. Data collected on different premises will be unsuitable or even impossible to compare in useful ways.

The AI tool developed for this study used AMA structure as a reference. Interestingly, very few specialists involved in tender projects use that structure for their work. It seems to be a traditional and well-structured way of specifying building requirements. Still, once the specialists have read the requirements, they put the information into more specific categories, like building part systems such as CoClass. AMA structure might help analyse the frequency of requirements and particular demands trends. Yet, that seems unsuitable for more holistic analysis - such as those that rely on data from project outcomes.

Moreover, the participants got notably less optimistic about the usefulness of extracting data from pdf files after seeing the demonstration. This, although at first surprising, might be explained by the increased awareness of the tool's limitations. However, it could also be a consequence of general pessimism towards the usefulness of the AMA structure. On the other hand, the participants got slightly more optimistic after the workshop regarding the benefits of benchmarking and tool implementation ease.

A significant challenge found in this study is creating trust for the software and evaluating its precision. A challenge identified in survey and workshop results is not losing the overall project perspective while using the tool and how to analyse what is not written. A human mind trained in handling tender projects also pays much attention to what is not written since great possibilities and risks can be hidden there. With an extensive database of requirements, it is possible to address this issue, but it is more challenging than analysing present client requirements.

The AI tool in this study extracted, analysed, and presented data to be used as a base for decision-making. However, if the tool had been trained to make the decisions, the trust issue would be even more crucial to address. Therefore, reflecting on which kind of decisions humans shall make, which kind shall be made by AI, and which kind shall be made in collaboration will be crucial for successfully using the technology [14].

One commonly desired future feature is scanning for and highlighting risks, like unsuitable combinations of technical requirements or products with high warranty issues. Enabling such a feature, knowledge transfer from production and aftermarket can generate incitements in the tender phase of new projects. Other possibilities within the area of risk assessment could be to find similarities with historical projects and use their risk/possibility outfall for having a statistical approach to risk assessment for new projects.

Nonetheless, despite all interesting future features brought up during the workshop, it seems that filtering out previous projects with similar requirements to use as reference in new tender projects is, in its most basic form, already perceived as helpful by tender practitioners.

In the workshop, the actual value of an AI tool was questioned in terms of works efficiency. Even though AI can make extensive data analyses faster, it might not automatically create a more effective work method. Therefore, it is essential to identify where AI can add business value and generate incitements for usage. Even if the work efficiency might not be significantly increased, the higher accuracy in AI-supported data-driven analysis can lead to cost savings, risk reductions, and more predictable production.

Interoperability, i.e., alignment of new digital technologies with existing IT, was also desirable. Interoperability is especially challenging for large organizations but an essential factor to consider when creating digitalization strategies and implementing new automated work methods.

Most opportunities and desired future features were within the field of benchmarking and filtering and sorting information. If this can be done to support the existing work method, the participants in this study seem to be optimistic about the ease of implementation.

6 Conclusions

In this study, we explored the potential of artificial intelligence tools in tender projects and identified challenges and possibilities with data-driven decision-making.

The results of this study show an overall high optimism towards implementing and using AI tools in the tender phase. The most significant potential for an AI tool in the tender phase was found in benchmarking, where the following opportunity areas were identified:

- Comparing project requirements with projects in an existing database
- Find hit-rates and key-performance indicators
- Categorizing, sorting, and filtering data
- Find high-risk products and technical solutions

Structuring the extracted data to facilitate decision-making is important for supporting the specialists' work in tender projects. However, how information should be sorted might vary depending on the intended use and should be studied further.

Identified main challenges to address for successful AI tool implementation found in this study are:

- Lack of standardization
- Need for new work methods

- Difficulties in interpreting results
- User interface and interoperability

AI and digitalization can assist the knowledge transfer from production and aftermarket to new tender projects. However, successfully using AI for generating business value requires higher levels of digitalization, creation of accessible, well-structured databases, as well as access to historical project data. Once this is achieved, AI can be powerful business support in early project phases

7 Acknowledgments

This research study has been financially supported by SBUF - the Swedish construction industry's organization for research and development.

The authors would like to thank Savantic for their contribution to the development of the AI tool.

A final thanks to NCC Building Sweden AB for all the helpful information about the tender process and the specialist participating in the tool evaluation.

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