THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Data-driven and production-oriented tendering design using artificial intelligence

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“Where is the Life we have lost in living?
Where is the wisdom we have lost in knowledge?
Where is the knowledge we have lost in information?”
The Rock, T. S. Eliot.

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Abstract

Construction projects are facing an increase in requirements since the projects are getting larger, more technology is integrated into the buildings, and new sustainability and CO_2 equivalent emissions requirements are introduced. As a result, requirement management quickly gets overwhelming, and instead of having systematic requirement management, the construction industry tends to trust craftsmanship. One method for a more systematic requirement management approach successful in other industries is the systems engineering approach, focusing on requirement decomposition and linking proper verifications and validations. This research project explores if a systems engineering approach, supported by natural language processing techniques, can enable more systematic requirement management in construction projects and facilitate knowledge transfer from completed projects to new tendering projects.

The first part of the project explores how project requirements can be extracted, digitised, and analysed in an automated way and how this can benefit the tendering specialists. The study is conducted by first developing a work support tool targeting tendering specialists and then evaluating the challenges and benefits of such a tool through a workshop and surveys.

The second part of the project explores inspection data generated in production software as a requirement and quality verification method. First, a dataset containing over 95000 production issues is examined to understand the data quality level of standardisation. Second, a survey addressing production specialists evaluates the current benefits of digital inspection reporting. Third, future benefits of using inspection data for knowledge transfers are explored by applying the Knowledge Discovery in Databases method and clustering techniques.

The results show that applying natural language processing techniques can be a helpful tool for analysing construction project requirements, facilitating the identification of essential requirements, and enabling benchmarking between projects. The results from the clustering process suggested in this thesis show that inspection data can be used as a knowledge base for future projects and quality improvement within a project-based organisation. However, higher data quality and standardisation would benefit the knowledge-generation process.

This research project provides insights into how artificial intelligence can facilitate knowledge transfer, enable data-informed design choices in tendering projects, and automate the requirements analysis in construction projects as a possible step towards more systematic requirements management.

Keywords: Systems engineering, Requirement management, Natural Language Processing, Inspections, Knowledge transfer

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Linda Cusumano

List of publications

Paper I

Cusumano, L., Saraiva, R., Rempling, R., Jockwer, R., Olsson, N., and Granath, M. (2022). Intelligent building contract tendering – potential and exploration.

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Paper II

Cusumano, L., Rempling, R., Jockwer, R., Saraiva, R., Granath, M., Olsson, N., and Okazawa, S. (2022). Natural language processing as work support in project tendering.

Presented at: *8th International Conference on Structural Engineering, Mechanics and Computation, SEMC 2022.*
Cape Town, South Africa, 5-7 September 2022.

Published in: Current Perspectives and New Directions in Mechanics, Modelling and Design of Structural Systems, September 2022, 978-1-003-34844-3 (ISBN), DOI: 10.1201/9781003348443-258.

Paper III

Cusumano, L., Farmakis, O., Granath, M., Olsson, N., Jockwer, R., and Rempling, R. (2023). Current benefits and future possibilities with digital inspection reporting.

Submitted for review to a scientific journal.

Additional relevant papers not included in this thesis.

[a] Desivyana, N., Farmakis, O., Cusumano, L., and Rempling, R. (2022). Challenges in the adoption of sustainable criteria in the Swedish property development industry. Presented at the *International Conference on Project MANagement 2022*, Lisbon, Portugal, 9-11 November 2022. Published in Procedia Computer Science, 219(1):1752-1759, 2023.

[b] Cusumano, L., Rempling, R., Olsson, N., Jockwer, R., and Granath, M. (2023). Systems engineering in the building construction industry: comparison with the telecom industry. Accepted for publication in *International Conference on Project MANagement 2023*, Porto, Portugal, 8-10 November 2023.

Terminology

In this research project, the following terms and definitions are used:

Term	Definition
AEC	Architecture, Engineering and Construction.
API	Application Programming Interface. Allows requesting data collected from an external source (in this project, Dalux Field) and generates a corresponding response.
After-sales	Production errors or warranty issues handled and discovered after the construction project is completed. Examples of warranty issues: leakages, unbalanced service systems, etc.
Artificial Intelligence:	"The science and engineering of making intelligent machines, especially intelligent computer programs". [1] Computer programs or systems designed to perform tasks that usually need human intelligence, like learning, reasoning, or interpreting.
Artificial Neural Networks	Neural networks compute real number representations inspired by the hierarchically organized neurons in the human brain [2]. ANNs comprise node layers containing one input layer, one or more hidden layers, and an output layer.
Buildability	Ease of construction [3] or the ability to construct a building efficiently, economically, and to agreed quality [4]. Factors affecting buildability are site conditions, safety, flexibility, standardization, assembly sequence, choice of materials and use of resources.
Data	Pictures, text, datasheets, tables etc. A collection of measured facts.
Deep Learning	The use of multilayer neural networks that compute with continuous representations [2].
Early Stages	"Early stages" in this research project are referred to as the tendering/bid phase and the conceptual design phase.
Embeddings	A mathematical approach to represent words, sentences, and documents.
Information	Structured and enriched data that has been given units and put into a context. Data can be measured, analysed, and visualized to create information.

Knowledge	Actions or decisions individuals or organisations make using historical data and information.
LLM	Large Language Model. Language model trained on large data using deep learning to perform NLP tasks.
Machine Learning	How computer agents can improve their perception, knowledge, thinking, or actions based on experiences or data [2].
NER	Named Entity Recognition. Techniques used within NLP to recognize entities like locations, organizations, persons and miscellaneous.
NLP	Natural Language Processing. A branch of artificial intelligence using computational techniques to understand the human language.
POS	Part-of-Speech tagging. Categorizing words in a text in correspondence with a particular part of speech, depending on the definition of the word and its context. A method often used to identify relationships between words.
Reinforced learning	A machine learning technique used for training AI models. It lets an agent learn action sequences that optimize its total reward [2].
Risk categories	Risk categories in construction projects • Environment *Extreme weather, pollution, noise, soil conditions.* • Economy *Risk for increased material prices, cost overruns, loss of profit, market and competition, import and export restrictions, and material scarcity.* • Time *Delays, productivity, availability of labour, unrealistic project time frame.* • Work safety and health *Incidents at the construction sites, stress-related health aspects, and psychosocial risks.* • Branding/Reputation *Damaged reputation, loss of business opportunities, loss of market share.* • Quality *Rework, poor workmanship, lack of technical knowledge.*
RNN	Recurrent Neural Networks. A type of artificial neural network using sequential or time series data. The output of RNNs depends on the prior elements within the sequence.

Supervised learning	A machine learning technique used for training AI models. The training set consists of input objects that are categorized according to a label.
Tendering	The process by which the client invites contractors to bid on a construction project.
Tendering Procurement	All documents (for example, technical descriptions and drawings) provided by the clients specifying the requirements of a specific project.
Tendering Design	The general design choices concerning the structural system, roof, exterior walls, installation system, production methods, etc., made in the tendering phase.
Tendering efficiency	Factors affecting the efficiency in the tendering phase: • Number of resources allocated in a tendering project (i.e., number of persons). • Time spent analysing client requirements. • Time spent collecting prices from subcontractors and suppliers. • Time spent analysing input from technical specialists/consultants. • Time spent calculating total price and production time. • Time spent in finding a suitable project organization. • Time spent in putting together tendering documents. • Time spent on risk analysis.
Tendering specialists	Various engineering disciplines involved in the bidding process on the contractor's behalf. Examples of specialist roles are structural engineers, sustainability experts, energy experts, geotechnical engineers, LCA specialists, cost estimators, etc.
Unsupervised learning	A machine learning technique used for training AI models. The training set only consists of input objects, and labelling is not required. The algorithm detects similarities and makes predictions [2].
Verification	An internal process that ensures whether a product/building/system is developed correctly or not and whether the designed product/building/system complies with requirements and regulations. The verification answers the question: “Are we building the product right?”
Validation	A process of checking whether a product/building/system has the right level of requirements and meets the operational needs of the stakeholders. It often involves the acceptance of an external customer. Validation answers the question, “Are we building the right product?”

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1 Introduction

1.1 Background

Construction projects are facing an increase in requirements since the projects are getting larger, more technology is integrated into the buildings, and new sustainability and CO_2 equivalent emission (CO_2e) requirements are introduced [5]. Today, the methods for analysing requirements are mainly manual, and as a result, requirement management quickly gets overwhelming. Instead of having systematic requirement management, the construction industry tends to trust craftsmanship [6]. More systematic requirement management in the construction industry could give benefits such as a better understanding of the project complexity, identification of requirement risks, and general quality improvement. Since project requirements tend to change during the project's progress, systematic requirements management could also provide requirement traceability, reducing the risk of insufficient building performance [6].

One approach to a more systematic requirements management found in other industries is systems engineering. Systems engineering is a transdisciplinary and integrative approach to enable successful project realisation, where the focus is on wholes and the synthesis of the whole from complementary parts [7], [8]. The function of system engineering can be defined as guiding the engineering of complex systems [9]. It focuses on an early definition and documentation of customer needs and then proceeds with design synthesis and system validation.

Combining requirements with verifications and validation with a systems engineering approach might enable new possibilities for knowledge transfer within the construction industry. When project requirements and verification data are digitised, new projects can benefit from previous project experiences.

Today, most information flows in a construction project are linear, with little data available at the project start and more and more data added during the various construction stages. After the production is completed, the project data is generally not further used. If, instead, a circular information flow can be achieved, see Figure 1, production, purchasing, and quality/warranty data can be used in early project stages, such as the business-critical tendering stage.

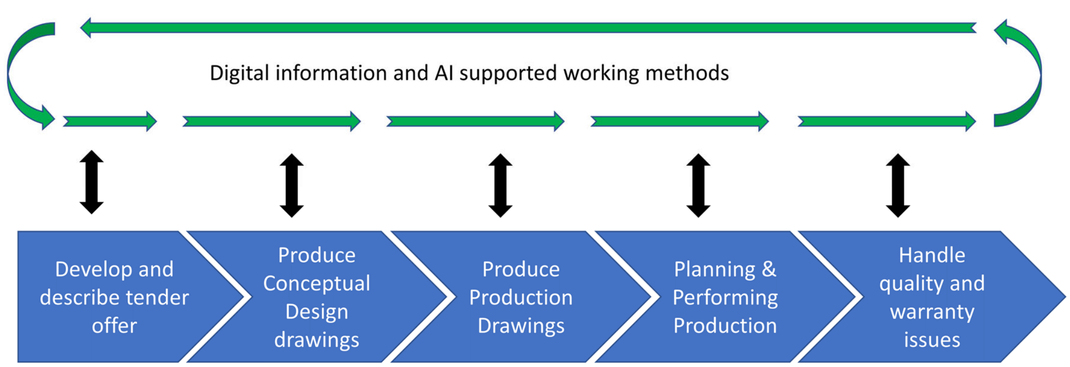

Figure 1. Circular information flows through the various stages of a construction project.

1.2 Purpose and objectives

The construction industry is requirement-oriented. However, a systematic approach to requirement management is missing due to the excessive manual workload today's methods demands. With the assumption that more requirements and production data will get digitalised within the near future, artificial intelligence can be a suitable technology for fast analysing vast amounts of data. Therefore, the purpose of this research project is to investigate how artificial intelligence can facilitate circular information flows from production to new tendering projects. The research project will also explore how circular information flows can enable data-informed decisions and knowledge transfer by using construction data for a systems engineering approach.

Since the construction industry is relatively novel in artificial intelligence adaptions, this research aims to explore artificial intelligence benefits in specific project phases and understand how potential users perceive the possibilities and challenges of using AI-based work support tools.

This research project aimed to answer the following main research questions:

RQ1: How can client requirements in the tendering phase be digitalised and analysed in a more automated way?

RQ2: How can production data be used in new projects?

RQ3: How can artificial intelligence be used to facilitate knowledge transfer?

1.3 Research outline

The first part of the research project targeted the requirement analysis made by the contractor in the tendering phase. Its position in the construction projects process is presented as Study A in Figure 2. The second part of the project focused on the verifications and validations made during the production phase, presented as Study B in Figure 2.

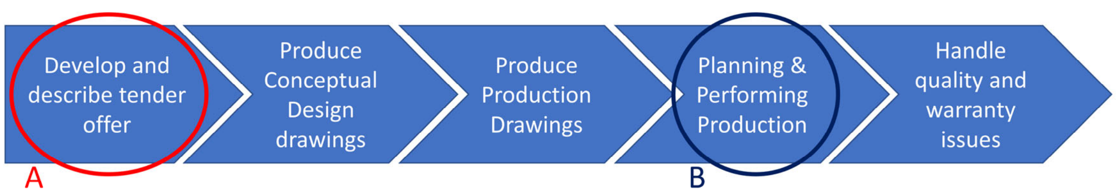

Figure 2. The focus of Study A and B in the construction process.

1.4 Limitations

The research project was limited to Design and Build contracts, where the contractor can influence the building design. In the other contract form, Design-Bid-Build contracts, the design is made on the client's behalf, which limits the contractor's influence. Therefore, this kind of contract was not included in the study.

The study only focused on housing projects (apartment buildings, office buildings, care homes, schools and preschools, industrial buildings) and not infrastructure projects since the majority of Swedish infrastructure projects have a different tendering process with only one public client.

This research project explored the possibility of applying artificial intelligence to construction industry data. The research was limited to using already existing algorithms and machine learning techniques. Due to the large number of text documents available in the construction industry, like meeting notes, technical descriptions, fire safety documentation, warranty issues, etc., this research project mainly focused on natural language processing, which is the branch within AI targeting text analysis. However, most techniques can also be applied to non-text data.

The study mainly targeted the Swedish construction industry. Still, the theories and results can be applied to the construction industry in other countries since they largely face the same challenges and possibilities. Furthermore, the study focuses on client and regulatory requirements and the process of analysing them, not on general market conditions or business approaches.

The knowledge transfer was investigated from a contractor perspective, focusing on reusing production data in early project phases, such as the tendering phase. The research explores possible methods for facilitating knowledge transfer based on digitalisation and artificial intelligence.

1.5 Outline of the thesis

This thesis consists of seven chapters and three appended scientific papers. The chapters are structured as follows:

Chapter 1: Introduction

The first chapter introduces the topic to be discussed. It refers to the study's purpose, research outline, and limitations, giving the reader a comprehensive view of the research.

Chapter 2: Frame of references

This chapter introduces Systems Engineering and Artificial Intelligence, focusing on natural language processing.

Chapter 3: Research methods

Chapter 3 presents the research methods used and how they were combined in the two studies.

Chapter 4: Results

Chapter 4 presents the main results from the two studies conducted.

Chapter 5: Discussion

In this chapter, the results are discussed, focusing on requirements analysis, knowledge transfer, and systems engineering.

Chapter 6: Conclusions

This chapter includes the author's thoughts that derive from the analysis of the results.

Chapter 7: Future work

This chapter proposes further possibilities for research.

1.6 Summary of appended papers

1.6.1 Paper I

Paper I presents the results from a workshop with tendering specialists. The workshop attendees participated in a demonstration of an AI tendering tool and afterwards discussed possibilities and challenges related to implementing such a tool as support. The results show optimism towards implementing AI tools in the tender phase. The most considerable possibilities were benchmarking new projects to previous projects, identifying key performance indicators and requirements risks, and enabling data sorting and filtering. Identified main challenges to address for successful AI tool implementation were the lack of standardisation, the need for new work methods, difficulties in interpreting results, and the desire for interoperability with existing software.

1.6.2 Paper II

Paper II explores the possibility of using natural language processing to analyse client requirements. Tendering specialists within a large Swedish contractor were asked to rate the usefulness of an AI tool as work support through two surveys. The results show that such a tool could be helpful support for tendering specialists, particularly for project benchmarking and risk management purposes.

1.6.3 Paper III

Paper III explores the usability of production data for knowledge generation. First, the present quality and usability of production data generated in an issue reporting software are investigated using a dataset containing over 95,000 production issues. Then, the benefits of digital inspection reporting for project members and projects are investigated by surveying various production specialists. The results show that there are project and project member incentives for digital inspection reporting, such as time savings, a smoother inspection process, and increased control and use of the 3D model. In addition, the results show that digital production data can be used for generating knowledge within a project-based organisation, but standardization of data collection, increasing data quality, and automation of the analysis process are necessary.

2 Frame of references

2.1 Systems engineering

This research project uses systems engineering as a theoretical framework, which is one approach to more systematic requirements management. Previous research indicated that the construction industry could benefit from a systems engineering approach to design since it helps focus on the complete project rather than its parts while fulfilling requirements [5].

2.1.1 What is systems engineering?

A common definition of systems engineering is: “a transdisciplinary and integrative approach to enable the successful realization, use, and retirement of engineered systems, using systems principles and concepts, and scientific, technological, and management methods” [7]. “Engineered systems” may be composed of people, products, services, information, processes, and natural elements, giving a broad sense of the term.

Even though there are system engineering definitions with slightly different contexts depending on the sector or industry, common for all is to focus on the whole from complementary parts [8]. A certain level of complexity is required, where the diversity of the elements in a complex system requires different engineering disciplines to be involved in their design and development [9].

The function of system engineering can be defined as guiding the engineering of complex systems [9]. It focuses on an early definition and documentation of customer needs and then proceeds with design synthesis and system validation [10]. Systems engineering includes the system's design and external factors such as customers' needs, the operational environment, interfacing systems, logistic supports, and personnel capabilities.

2.1.2 The origin of systems engineering

The recognition of systems engineering as an activity was greatly accelerated during World War II when the need to engineer functional systems that spanned different engineering disciplines increased [5], [8], [9]. The demand arose from the advancement of technology and the development of high-performance aircraft, military radar and missiles, and the atomic bomb. Technology advancement and compressed time schedules required new approaches in program planning, technical coordination, and engineering management [9].

Several books were published in the 1950s and 1960s, identifying systems engineering as a distinct discipline [11]. The early SE projects were primarily military and space-based [12], and the philosophy of systems engineering was developed mainly at NASA in the 1960s and 1970s [5], [8]. In 1983, The Defence Systems Management College in the US produced a SE management guide [13], describing the various steps, starting with the requirement analysis and ending in the synthesis of alternative solutions [5].

In 1990, The International Council on Systems Engineering (INCOSE) was founded in the US. INCOSE is a non-profit membership organisation aiming to develop and disseminate the transdisciplinary principles and practices that enable the realization of successful systems. They are today a leading international actor in modern Systems Engineering development [7].

2.1.3 The V-model

A V-model commonly visualises the systems engineering approach. The V-model envisions the development within a complex system, where the left-wing consists of requirement and solution decomposition [14]. Parallel with the requirements decomposition in the left-wing, the V-model's right-wing represents a verification and validation process. Continuous verification and validation ensure the chosen design and built solution meet the expected requirements. Each step in the verification and validation process should correspond to the same requirement step in the left wing of the V-model. This research defines verification as actions to ensure the design and engineered solutions comply with the project goals, objectives, and requirements. The verification aims to answer the question, "Are we building the building right?". The verification involves activities like drawing reviews, testing, mockups, and simulations. Validation is defined as the process of controlling whether the completed building fulfils the client's needs and the functional requirements. The validation tries to answer the question, "Are we building the right building?". The validation involves activities like inspections, testing of fire safety systems, and coordinated testing of heating and ventilation systems.

Figure 3 shows a V-model adapted to the construction industry for projects with design-and-build contracts. The author developed the model and discussed and refined it during a digital workshop with construction industry representatives [15].

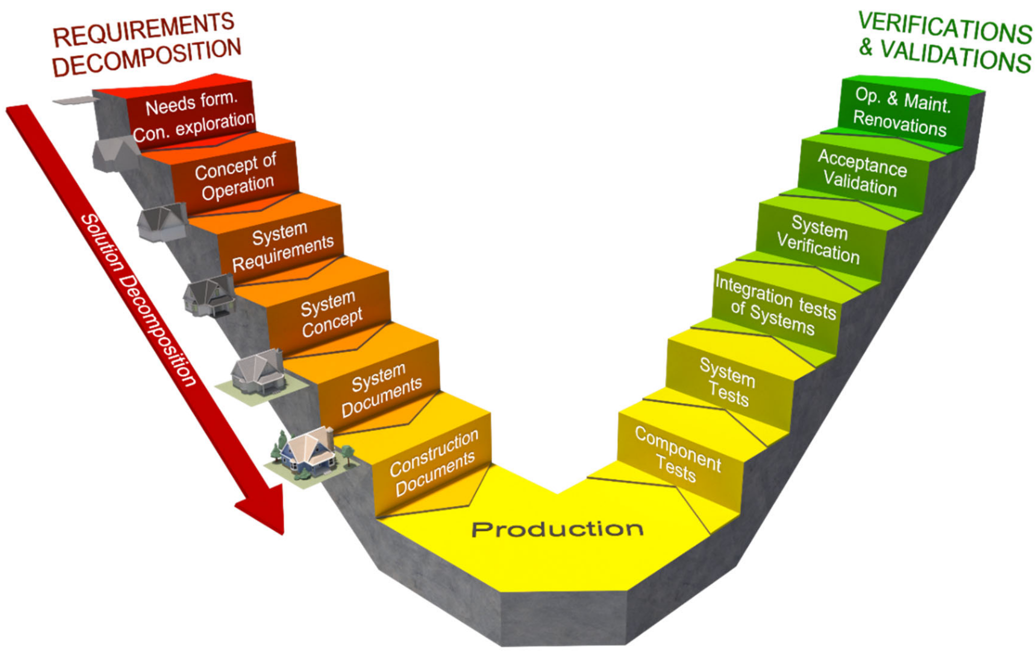

Figure 3. V-diagram for sequential systems engineering lifecycle in construction. The left-wing symbolises the various steps in the requirements and solution decomposition, getting more detailed for each step. The right-wing represents the corresponding verifications and validations.

The model shall be read starting from the top left corner, beginning with the need formulation, then proceeding step by step down the left requirements specification stair until the production phase begins. The requirements specification and solution decomposition reach a higher detailing for each step-down. Parallel with the solution decomposition, requirements are continuously verified for the designed solution. Starting in the production and ascending the right stair, verifications and validations align with the corresponding requirement/solution level on the left stair.

The first step, in the upper left corner of the V-model, presented in Figure 3, is formulating a need and problem description. The purpose of the initial step is to justify initiating a new project and understand which perceived needs the project must fulfil. The output from the need analysis is a description of system capabilities that serve as input to the next step, the concept exploration and feasibility study.

The client performs the concept exploration, often assisted by an architect. Here, the main focus is on the business and user needs and converting the operationally oriented requirements into functions the building must have. An example of a requirement document developed is the room function program, where the client describes which functions are required in each building room. An essential part of this step is the feasibility analysis to understand if any conceptual designs can fulfil the operational objectives. The feasibility analysis includes the site's physical environment, risks, and cost considerations.

Step two is to define the concept of operation, which is a broad description of how the building should be operated in the future and which capabilities it shall have from the viewpoint of the future individual user. The operation concept shall include the purpose of the building and the scope, for example, a residential building with six floors and 24 apartments. It shall also present an overview of the building's layout, architectural design and key features. Users, operators, and stakeholders shall be identified, and the operational environment defined. For an apartment project, the users are the prospective tenants, the operators are the landlord and the service management team, and other stakeholders can be the municipality, nearby businesses, consultants and subcontractors involved in the development, and service suppliers. The operational environment includes site conditions, weather conditions, regulatory requirements, infrastructure restraints, and technology integration. The building's future maintenance needs and strategies shall briefly be described. Constraints like maximum building height and geotechnical conditions shall also be considered.

In Step three, the results from the concept of operation document are used to develop system performance requirements. In this phase, the functional characteristics are refined, and the overall purpose is to answer the question, “What shall the building be able to do?” Important factors specified in this phase are acoustic requirements, indoor climate requirements, fire safety requirements and sustainability requirements. The requirements developed in Steps one, two and three are provided in the tendering procurement.

Step four happens after the project tendering when a contractor is on board. In this step, the focus is the System concept, trying to answer the question, “How shall the building do it?” Here, a conceptual design of the building is made, where requirements are further specified and developed. Choices regarding materials and dimensions are made, and alternative solutions are investigated. When comparing the construction industry to other industries, the system concept phase is somewhat different since it might include a significant amount of concept exploration. Particularly in design-bid-build contracts, the contractor greatly impacts the preferred system and conceptual design solution choice. In other industries, the primary concept exploration is made in the first step, whereas this is mainly true in the construction industry for bid-build contracts, where the client is fully responsible for the system choices and the design.

Step five shall result in system documentation, focusing on subsystems. This step develops the requirements and design regarding ventilation, plumbing, heating, structural framework, electricity, etc. The result from Step five is conceptual design drawings and documents specific enough to give a good estimation of the complete project cost. The drawings also provide a baseline for contracts with sub-contractors and suppliers.

The final step, "Construction documents," focuses on components. In this step, the requirements and designed solution have reached a components level, and all drawings and documentation needed to start the production are finalised. The drawings and documentation are very detailed, and all components, such as beams, bolts, air ducts, etc., are specified.

All steps, their purpose and which stakeholder has the primary responsibility for the requirements specification in each specific step are presented in Table 1. The responsible actor might vary slightly in projects with early involvement from the contractor. In early involvement contracts, the contractor takes a larger role in formulating the system requirements in step three and sometimes even in defining the concept of operations in step two.

During a workshop and interviews with specialists within the construction industry, the process visualized by the V-model felt familiar, and no obstacles to adopting a systems engineering approach were identified [15]. However, the process similarity lies mainly in the steps for refining the chosen design solution and not in the requirements decomposition. Therefore, adding a more systematic requirement analysis and decomposition and carefully selecting proper verifications and validations is essential for SE adoption in the construction industry.

Table 1. Steps in the V-model, their purpose and responsible actor in design & build contracts

Step	Name	Purpose	Resp. actor
1a	Problem/Need formulation	Needs analysis and justification of development	Client
1b	Concept exploration & feasibility analysis	What performance is required to meet the perceived need? Is there a feasible approach to achieve such performance at an affordable cost?	Client
2	Concept of operations	How shall the building be operated from the viewpoint of the business & users?	Client
3	System requirements	What should the building be able to do?	Client
4	System concept	How shall the building do it?	Contractor
5	System documentation	Specifying subsystems like ventilation, structural framework, heating, etc.	Contractor
6	Construction documents	Specifying components like beams, columns, ventilation units, fixtures & fittings, etc.	Contractor

2.1.4 Systems engineering in the construction industry

During the last 15 years, there has been increased interest in Systems Engineering in the construction industry. Research and implementations have mainly been made within large infrastructure projects. Aslaksen et al. [6] identified advantages such as requirement transparency, a better understanding of roles and better contracts, with SE applied in construction projects. In 2012, Eames and Marjanovic-Halburd [5] claimed potential improvements for the construction industry if adopting a system engineering approach similar to the spacecraft industry.

In the Netherlands, Meertins et al. developed a Systems Engineering framework for facilitating the involvement of all actors and stakeholders of a construction project [16]. INCOSE also created a guide for applying Systems engineering in large infrastructure projects in 2012 [17]. The Norwegian construction industry has attempted a systems engineering approach under the name “Systematic Completion” [18], [19]. A pre-study concerning systematic requirement management in the Swedish construction industry was performed in 2019 and further investigated in 2021 [20], [14], showing an increased interest in a systems engineering approach in Sweden.

Emes et al. [5] and Graaf et al. [10] have identified validation problems within the construction industry. Since the ability to build and test prototypes is limited, it is difficult for construction projects to get feedback regarding the end product quality relative to the customer expectations until it is economically too late to address significant shortcomings [5]. Yahiaoui et al. [21] argue that adoption of the traditional V-model during the building design and construction process would help optimise the trade-offs during the building lifecycle since it allows for the transformation of operational needs into a system performance parameters specification and integration of different functionalities requirements and related design parameters.

Systems engineering has been present in other industries mainly since the 90s, but the construction industry hasn’t adopted it to any considerable extent. One explanation given by Aslaksen et al. [6] is the construction industry’s traditional trust in craftsmanship, making the process from plan to project largely implicit. Therefore, requirements breakdown, verification, and validation have not been considered as crucial as in other industries. Another explanation is found in the requirements. The requirement specifications differ when comparing the construction industry to other sectors practising systems engineering, like the aerospace and defence industry. In other sectors, the project complexity is often derived from the complexity of the customers’ requirements. But, in a traditional construction project, the requirements are relatively simple, and the design follows rigid standards. The complexity lies instead in the process of creating the building and the construction work itself [6]. Relatively little money is spent on the design of a traditional construction project compared to other industries. Consequently, the construction industry tends to focus on creation rather than design [6].

Due to the discipline-oriented structure of the design and production works, one significant challenge with the implementation of SE in the Swedish construction industry is that the flow-down of requirements (left-wing in the V-model) happens across contractual boundaries. This means that different firms often complete the system elements at different times [22]. Therefore, most engineering efforts are spent on designing the work instead of the systems [6].

The codes, standards, and local municipality regulations that form part of the requirements add another layer of complexity to construction projects, leading to varying and sometimes conflicting requirements. Municipalities, clients and inspectors also interpret the regulatory requirements differently, leading to a lack of standardisation in the performance and content of control plans and self-inspections [23].

Despite the identified challenges, SE has several potential benefits in construction [5]. Adopting a systems engineering approach in the housing construction industry intends to achieve objectives like minimization of risks, improved quality predictability, and improved communication between stakeholders. Digitalisation and new technologies might also enable a more successful SE implementation.

2.2 Artificial intelligence

2.2.1 What is artificial intelligence?

Artificial intelligence (AI) refers to the development of computer systems and programs that can perform tasks that would typically require human intelligence, such as learning, problem-solving, decision-making, and language processing. AI systems are designed to learn from data and improve over time without being explicitly programmed to do so [1].

2.2.2 The origin of artificial intelligence

The English mathematician Alan Turing is seen as one of the first to work with artificial intelligence. In 1947, he gave a lecture about intelligent machines, and in 1950, he published a paper titled "Computing Machinery and Intelligence" [24]. Another milestone in the history of AI was a conference hosted by John McCarthy and Marvin Minskey in 1956, the "Dartmouth Summer Research Project on Artificial Intelligence" (DSRPAI). The conference brought together top researchers from various fields to discuss artificial intelligence, a term first used during this conference [25].

From 1956 forward, AI continued to flourish. Computers got faster and could store more information. Therefore, AI was predicted to have a bright future and received much funding from government agencies such as the Defense Advanced Research Projects Agency [25]. However, in 1969, Marvin Minsky and Seymour Papert published a book highlighting the limitations of simple neural networks [26], and soon after, Hans Moravec, a doctoral student of McCarthy, stated that computers were still much too weak to exhibit intelligence. This reduced funding and limited research for ten years [25].

In the 1980s, AI had again a rapid growth thanks to the expansion of the algorithm toolkit and a boost of funds. A form of AI program called "expert systems", which mimicked the human decision-making process, was adopted by corporations worldwide, and knowledge became the focus of mainstream AI research. The Japanese government heavily funded expert systems development for their Fifth Generation Computer Project. Countries like the UK and the USA responded with their programs. During this period, there was also a significant development of neural networks, which would become commercially successful in the 1990s. However, the market for specialized AI hardware collapsed because of the gain in speed and power of desktop computers from Apple and IBM. One of the most successful expert systems, XCON, proved too expensive to maintain. By 1991, most of the ambitious goals in the Fifth Generation Computer Project had not been met, and over 300 AI companies had to shut down [25], [27] [28].

In 1997, Deep Blue became the first computer chess-playing program to beat the world chess champion Gary Kasparov, and in 2011, IBM's question-answering system Watson defeated the two greatest Jeopardy champions, Brad Rutter and Ken Jennings. Those successes were mainly based on increased computer processing speed and storage capacity [27], [29].

In the first decade of the 21st century, AI continues to develop due to access to "big data", cheaper and faster computers and advances in machine learning techniques [25]. Advances in deep learning, particularly convolutional neural networks and recurrent neural networks, have led to considerable progress in applications like image and video processing, text analysis and speech recognition [30].

2.2.3 Natural language processing

Natural Language Processing (NLP) is a computer's use of human language [31]. NLP is a transdisciplinary AI field, including computational linguistics and computer science. There were early attempts at using machines to translate text in the 1930s [32]. However, technology took a step forward during World War II with the German encrypting machine Enigma and Alan Turing’s deciphering machine The Bombe [32]. In 1949, the American scientist and mathematician Warren Weaver wrote a memorandum titled “Translation”, where he resonated about the possibility of using digital computers to translate documents [33]. Two years later, in 1957, Noam Chomsky published his book “Syntactic Structures”, where he created a style of grammar called Phase-Structure Grammar, which translated natural human language into a computer-usable format [34]. In the IBM-Georgetown Demonstration of 1954, an automatic text translation program was presented, successfully translating sixty Russian sentences into English. The translation was done by mapping sentences and using a dictionary. In the same year, the journal of Mechanical Translation began publication [35]. In the 1960s, a milestone within NLP was reached by Terry Winograd at the Massachusetts Institute of Technology when he developed a machine able to perform tasks like moving objects, determining the current state and remembering names in a block world environment [32]. Most of the NLP research in this period focused on syntax and had dictionary-based word-to-word processing [35]. However, Plath et al. [36] showed an increased need to solve the semantic problems of NLP.

In 1966, the publication of the Automatic Language Processing Advisory Committee (ALPAC) report almost killed all machine translation research [37]. The report concluded that machine translation was nowhere near achievement and led to funding cuts, particularly in the USA [35].

Roger Schank introduced the concept of tokens in 1969 [38]. The concept gave a better grasp of the meaning of a sentence and provided the machine with better insights into the things happening and the involved objects.

Until the 1980s, most of the NLP systems used complex handwritten rules, but in the late 1980s, an increase in computational power and the introduction of machine learning made NLP go from handwritten rules into concept-making [32]. Algorithms like decision trees were used to deduce the optimal result and were backed up with probabilistic algorithms. These statistical models gained popularity, and in the 1990s, their use rose dramatically. In 1995, George A. Miller presented the paper “WordNet: A Lexical Database for English” [39]. WordNet is an extensive lexical database that organizes words into sets of synonyms and provides a semantic relation between them.

However, using rules and fixed criteria for machine translations was still challenging, leading to a shift towards deep learning. Deep learning could efficiently solve the problem of one word having different meanings depending on its neighbouring situation. It does not require a programmer to provide the rules since the algorithms themselves deduce the process of mapping an input to an output [32]. In 2003, Yoshio Bengio introduced the first neural language model [40], and in 2013, Word2Vec was introduced by Tomas Mikolov [41]. Word2Vec is a language model using a neural network to learn distributed word representations [41].

The capabilities of language models have grown mainly due to the availability of large amounts of digital training data provided by the internet and having sufficient hardware. A significant step in the NLP field was also made in 2017 when Vaswani et al. [42] wrote, “Attention is all you need”, introducing transformer models and the concept of attention. Previously, the most common approach for performing neural machine translations was using Recurrent Neural Networks (RNNs). However, their architecture had a significant limitation when working on long sentences. This problem was solved with the attention mechanism, allowing the extraction of information from the whole sentence. The transformer model extracts features for each word in a sentence and figures out the words' importance. While RNNs process sequences sequentially, a transformer model can process the input sequence in parallel, making it more efficient. Another significant benefit of transformer models is their enabling of transfer learning. A transformer model can be pre-trained on large amounts of unlabelled text and later fine-tuned on specific smaller tasks. This possibility shortens the invested time and effort for an NLP project significantly.

Lately, the use of transformer language models pre-trained on large amounts of unlabelled data has increased. BERT [43] is one of the most commonly used state-of-the-art models, appreciated for its fine-tuning abilities, allowing the model to tackle a broad set of NLP tasks successfully. In March 2023, the multimodal transformer model GPT-4 by Open-AI was released [44]. The model quickly became popular due to its good performance, ability to handle both text and images and the possibility to test the model for free online.

2.2.4 Areas of application of natural language processing

The development and use of NLP continue to grow, and today, NLP is used for a variety of tasks, such as:

- **Machine translations**: translating a sentence, text, or document from one language to another.
- **Text classification**: the process of understanding the meaning of unstructured text and organizing it into predefined categories.
- **Semantic analysis**: analyses the sentence structure, word interactions and related concepts to discover the meaning of the words and understand the topic.
- **Text summarizations**: summarizing the most important information in large text.
- **Token classification**: Named Entity Recognition (NER) models for identifying persons, organizations, locations, etc.
- **Question answering**: Answering questions based on large text corpora or tables.
- **Text generation**: the process of generating sentences, texts, code, etc.
- **Text similarity**: compares sentences or full documents and generates a similarity score.

2.2.5 Natural language processing in the construction industry

Research regarding NLP applications within the construction industry has mainly focused on project monitoring, work safety, risk management, BIM and compliance, and document management [45].

2.2.5.1 Project monitoring

Attempts to use NLP in the construction industry to monitor project performances have been successful. Marzouk and Enaba [45] used NLP techniques to analyse and monitor construction contracts and correspondence. Their study examined word and term frequency in contracts and outgoing correspondence from the client to the contractor, enabling the identification of delays or other problems occurring during production.

2.2.5.2 Work safety

Work safety monitoring has been the target of several studies. For example, Tixier et al. [46] used NLP to extract precursors and outcomes from unstructured injury reports. Shayboun [47] used machine learning to classify the severity of work accidents reported by a Swedish contractor. Her study shows that the technology works but that the data often is too unspecific regarding the cause of the accident. Lin et al. [48] used key-word extraction and topic modelling to understand work safety incidents reported during the production of Chinese construction projects.

2.2.5.3 Risk management

Zou et al. [49] developed a model for estimating risks by analysing risk case documents within a contractor company. The risks mainly concerned work safety but also structural, design, and quality risks. Risks connected to lack of accuracy in bidding documents were investigated by Lee and Yi [50]. By performing text mining on pre-bid documents and using the results to influence the risk prediction, they could reach a much higher prediction accuracy than only using numeric data. Risks in terms of cost overruns have also been of interest to the construction industry. Most studies use AI applied to numerical data [51], [52], but there have also been studies using both numerical and text data to predict cost overruns. [53].

2.2.5.4 BIM and compliance

Today, BIM is an essential tool within the construction industry and is a target for AI applications. Yarmohammadi et al. [54] extracted text from BIM logs to predict the design performances by analysing the time consumption. Zhang and El-Gohary [55] developed a system using NLP to extract regulatory requirements and check their compliance with the BIM model. Their method showed high reliability, but the most significant challenge was correctly extracting the regulatory requirement text. Further exploring text-extracting possibilities for regulatory requirements, Xue et al. [56] investigated the possibility of extracting regulatory requirements in building codes by using Part-of-Speech tagging (POS), and their method proved to be useful when working with domain-specific text and needing to increase the accuracy of correct tagging.

Even though BIM models are also used in production, 2D drawing still plays an essential role in information visualisation. Finding the needed drawing in large projects or extensive drawing archives can be challenging. Yu and Hsu [57] suggested vector space models for retrieving CAD documents based on their textual content to simplify the process.

2.2.5.5 Document management

Shen et al. [58] used text-mining techniques to assist decision-making in green building design. Their work compared similarities in case reports from finished projects with features from new projects, using those similarities to retrieve documents from existing successful projects in a database. Al Qady and Kandil [59] applied clustering techniques for grouping construction documents based on similarity. Studies like Fan et al. [60] focused on developing a framework for retrieving projects-wide as-needed information from unstructured construction documents using the WordNet dictionary.

3 Research methods

This research project used a combination of methods with an exploratory objective in terms of applying technology for automating data collection and analysis. Where the two studies conducted are positioned in the construction process is presented in Figure 2.

3.1 Study A: Requirements analysis

Study A explored automation possibilities for requirements management, the left-wing in the V-model. Therefore, the first part of the research project zoomed in on the requirements analysis made by the contractor in the tendering phase. Targeting the tendering phase was motivated by many essential system choices in this early project phase, often with limited time. Consequently, automation can lead to favourable time savings for the contractor's tendering work.

To get a general understanding of the requirements provided in the tendering procurements, a pre-study of tendering procurements from 22 building construction projects was made. The analysis focused on available documents and data format. The analysed procurements were randomly selected from a database of tendering projects handled from 2017 to 2020 by a large Swedish contractor. The projects were school and preschool buildings, office buildings, apartment buildings, and care home buildings. The results from the pre-study were used for choosing how to tune the tool development in Step 1, Figure 4.

The outline of the requirement study is presented in Figure 4. The results are presented in Paper I and Paper II. Paper I used a qualitative data collection approach, whereas Paper II used a quantitative data collection approach through two surveys.

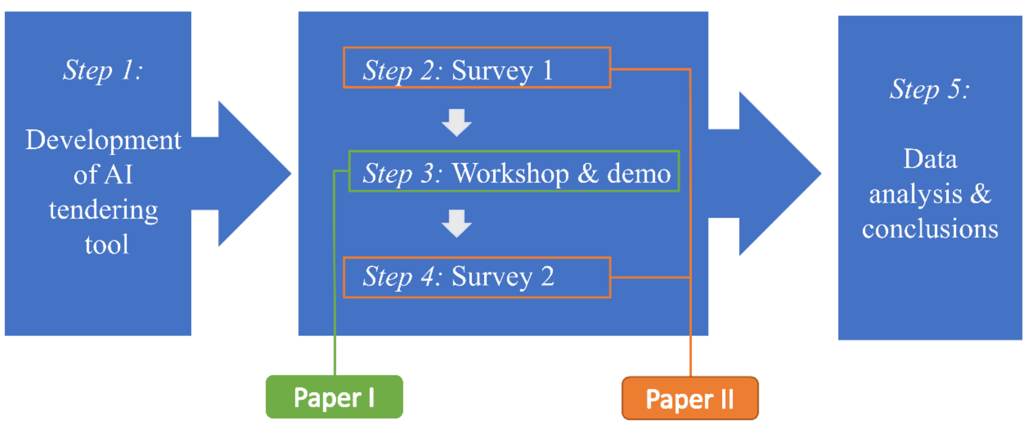

Figure 4. Outline of requirement analysis study. Paper I focuses on the workshop results, whereas Paper II presents the results from the two surveys.

3.1.1 Development of AI tendering tool (Paper II)

Since the research project wanted to explore possible NLP techniques suitable for requirements analysis and evaluate the usefulness of automated requirements extraction, the method choice was to develop and demonstrate an artificial intelligence tendering tool. The need for tool development was motivated by the difficulties in evaluating the usefulness of such a tool without demonstrating its capabilities since the present NLP knowledge in the construction industry is low. The tool demonstration enabled further investigations of the benefits and challenges connected to such tools implemented in the tendering process.

The architecture of the AI tendering tool developed in the first study is schematically presented in Figure 5.

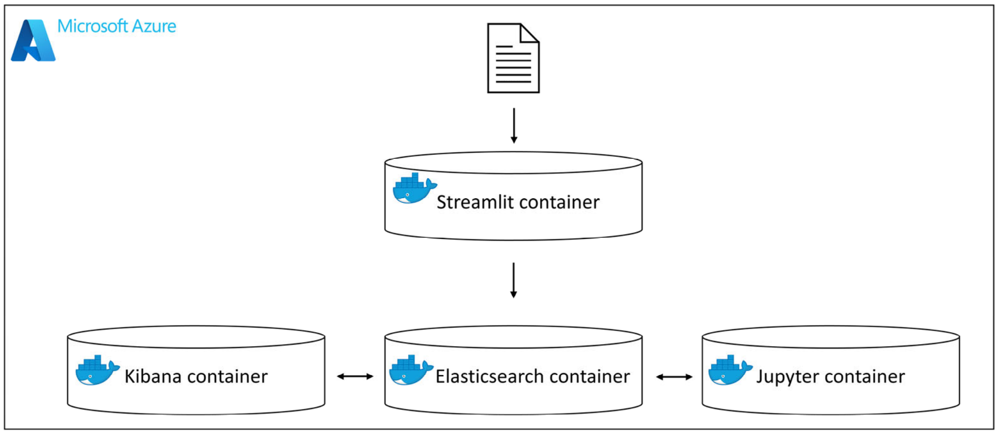

Figure 5. Architecture of AI tendering tool. Documents get scanned and uploaded to Elasticsearch using a Streamlit dashboard. The data can be analysed and visualised using Kibana. The Jupyter container is used for development purposes only.

A Streamlit dashboard was used as a web interface for scanning and uploading new documents and for comparing documents and texts. Since the documents came from various clients and had different designs, the selection of text area to extract was made by making the user draw a boundary box. This way, unwanted text like document template numbers, page headers, and footers could be omitted. The script for extracting the text was made in Python.

The extracted text was labelled with AMA codes since this is the most common layout for Swedish technical description documents. AMA-HUS is a handbook facilitating the formulation of material and performance requirements in technical building descriptions [61].

The pre-trained language model Word2vec [41] was used for processing the extracted text. The Word2Vec algorithm uses a two-layer neural network model that transforms the words into numeric vectors to learn word association from the extracted text. The dimensionality of the word vectors was set to 100. The model was trained on the "Swedish CoNLL17 corpus" dictionary repository, containing frequently used Swedish words. After transforming the words into vectors, the average word vector for each sentence was calculated by averaging and normalizing the word vectors. The similarity between two sentence vectors was obtained by calculating the inner product, generating a cosine similarity. The closer the cosine similarity is to 1, the more similar are the word vectors. A depiction of cosine similarity between vectors can be seen in Figure 6. The vectorization enabled comparing different uploaded documents with each other, both on the AMA code level and on the whole document level.

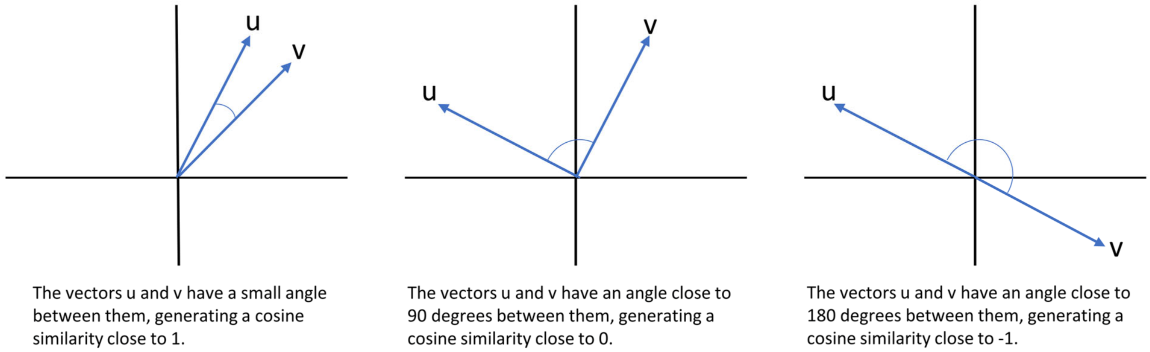

Figure 6. Depiction of cosine similarity for text vectors. The more similar the word vectors are to each other, the closer the cosine similarity is to 1.

Data from the extracted text was uploaded to Elasticsearch [62], an open search and analytics engine for all types of data, but in this case, it was used for text search and analysis. To allow the users to explore and analyse the data in Elasticsearch, Kibana was used as a web-based dashboard. Kibana is a free, open user interface with various powerful visualization possibilities [63].

The data used for test-running the AI tool was the technical building descriptions found in the tendering procurements analysed in the pre-study. The choice of developing the tool to extract text from technical building descriptions was because it was the most frequently appearing text document in the procurements.

3.1.2 Workshop design (Paper I)

A workshop was chosen to evaluate the usefulness of the AI tendering tool and collect qualitative data. Since the research was conducted during the COVID-19 pandemic, the workshop was hosted digitally on Teams. The workshop participants were selected since they were the intended future users of such a tool, working frequently in tendering projects for a large Swedish contractor. The workshop had 56 participants, representing the specialist roles of geotechnicians, structural engineers, energy specialists, LCA and sustainability engineers, building service engineers and cost estimators.

As an introduction to the workshop, there was a video demonstration of the AI tool prototype. Participants were then divided into groups of 5-6 members of similar discipline specialisations and invited to make notes of their thoughts and comments in the web-based whiteboard software Miro [64]. After the group discussions, the participants were asked to cluster their notes into the following categories:

- Challenges
- Opportunities
- Future Features
- Needed actions to achieve these opportunities.

The choice of categories was inspired by the concept of "Future workshops" by Jungk and Müllert [65]. This specific research design was motivated by previous research projects successfully applying it to explore new technologies [66].

After the workshop, the participants' comments collected in Miro were further analysed and clustered into themes. The analysis was made by manually reading all notes and identifying topic themes. In the category "Challenges", the four themes "standardisation", "user interface", "work efficiency", and "benchmarking" were identified. In the category "Opportunities", the identified themes were "knowledge", "risk/quality", "work efficiency", and "benchmarking". For "Future Features", the themes were "document types", "interoperability", "filtering and sorting", and "benchmarking". For the last category, "Needed actions", only three answer themes were identified, and those were "data access"," databases" and "digitalization".

3.1.3 Survey design (Paper II)

Since the demonstration of the AI tool might have caused changes in the attitude towards the AI tendering tool, a pre-and post-workshop survey was sent to the workshop participants to monitor possible changes. The surveys also enabled receiving individual responses, which was not noticed in the workshop data.

Both surveys were conducted as online self-completed questionnaires. The pre-workshop survey was sent by email to 59 people who had accepted the workshop invitation. The post-workshop survey was sent out to people who had answered the pre-workshop survey and participated in the workshop directly after the workshop was completed.

Both surveys were designed in the same way, consisting of three parts, where the first part addressed the background of the respondents. The second part assessed the perceived usefulness of the AI tool by asking closed-answer questions designed with a five-point Likert scale.

The following questions were asked in the survey's second part:

Q1: Imagine that, during your tendering work, you had access to a tool that automatically extracts the requirements in the procurement documents and organises the requirements into a desired structure. How useful do you think such a tool would be for you?

Q2: Into which structure would you prefer the requirements to be organised?

Q3: If you would have access to a tool allowing you to filter essential requirements and provide you with a list of previous projects with similar requirements, to what extent do you agree such a tool would be useful?

Q4: Considering the procurement documents you mainly analyse, to what extent do you agree that an AI tool could be used for supporting analysis?

In the third and last part of the two surveys, the respondents were asked to identify challenges, opportunities, desired future features, and actions needed before implementing such a tool. The questions were designed as open-answer questions and were identical to the workshop categories, enabling results comparisons. The comments received in open-answer survey questions were analysed similarly to the workshop comments by adding them into Miro and manually clustering them into themes.

3.2 Study B: Verifications & Validations

The essential verification and validation process parallels the requirements specification in the systems engineering approach. A well-performed verification and validation process can help minimise risk and reduce quality and performance flaws. The verification and validation data can also serve as valuable input into the early phases of new projects. Therefore, the second part of the research project zoomed in on the verification- and validation methods during the production phase, exploring knowledge transfer possibilities. The outline of this study is presented in Figure 7.

The data collection approach in Paper III was quantitative through a self-completion online survey and qualitative through interviews.

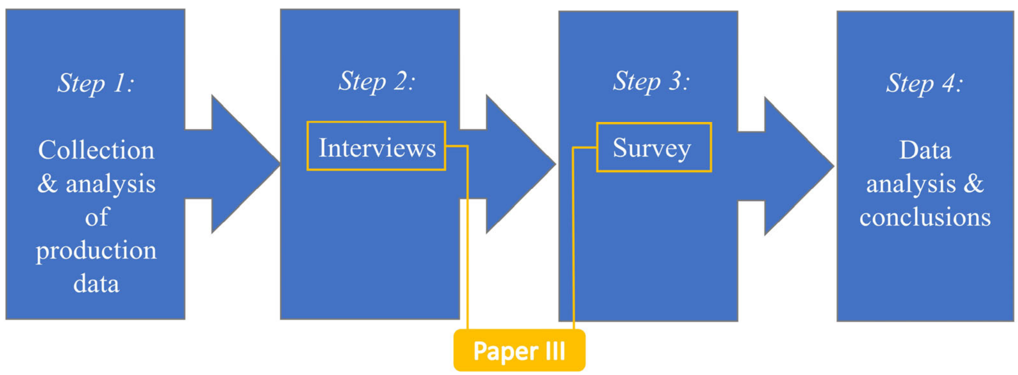

Figure 7. Outline of verification and validation in production study. Paper III presents the results of interviews and a survey.

Before starting the verification and validation data study, a pre-study was performed on four production data areas. The four identified areas were moisture measurements in concrete floors, after-sales and warranty issues, risk assessment data, and digital field inspection data. Their potential was evaluated considering the present amount of available data, future amount of data, collection methods and usability. The digital inspection data had the highest level of digitalisation, the largest current data volume, and high usability and was therefore selected for the study.

3.2.1 Collection of production data (Paper III)

For analysing the current state of the art of digital issue reporting, a dataset of inspection data registered in the software Dalux Field [67] was collected using and modifying existing APIs. The dataset contained 100928 production issues from 117 Swedish construction projects a large Swedish contractor performed during 2018-2021. The studied projects had an estimated production cost of 50 to 1800 million SEK. The production issues were registered using tablets or mobile phones by 507 users employed by the main contractor, sub-contractors, clients, and inspection companies.

The data set was enriched by adding data from different sources for easier pattern extraction and interpretation. Examples of enriched project data are predicted total cost, the main building activity (i.e., office, school, apartment, etc.), contract type (Design-Bid-Build or Design-Build), and if the project followed any internal contractor design standard. In addition, time plans in the form of Gantt charts were collected. The Gantt charts and time plans were then plotted on top of each other to monitor how the production problem frequency varied along the project progress and for possible pattern recognition and project progress monitoring.

Studying the dataset gave insights into how production problems were reported, which issues were reported, and which data was available for further analysis. The dataset interpretation was enriched by the interviews presented in Table 2.

3.2.2 Interviews (Paper III)

For Study B, six semi-structured interviews were performed as a survey preparation and data interpretation enrichment. The interviewees were experts in various domains related to inspection data. Table 2 presents the interviewees' business roles, where they were employed, and which focus the interviews had. The first four interviews focused on current and future project objectives with digital inspection reporting and interpretations of issue reporting patterns. The last two interviews focused on knowledge generation and organisation objectives.

Table 2. Interviews, business roles of interviewees, and interview focus.

Interview	Interviewees business role	Employer	Interview Focus
1	Production Supervisor	Contractor	Project objectives with digital reporting
2	Production Supervisor	Contractor	Project objectives with digital reporting
3	Sales manager	Insp. Software Developer	Differences in software uses
4	Project manager	Contractor	Project objectives with digital reporting
5a	VDC manager	Contractor	Knowledge generation
5b	VDC specialist	Contractor	Knowledge generation
6	NLP specialist	AI Company	AI-supported knowledge gen.

All interviews were conducted digitally using Teams and lasted 1-2 hours. The interviews were recorded and later transcribed. At interview five, two persons were interviewed at the same time.

The interviewees were asked about how they performed digital issue reporting, incentives, benefits and challenges, existing guidelines, and if they performed any further analysis of the collected data. Interviewee three was also asked about differences in how issues are reported between individuals, projects, companies and countries. The last interview focused on data analysis techniques suitable for the specific dataset.

3.2.3 Survey (Paper III)

The findings during the interviews were used to design an online survey to assess project and project member benefits and future possibilities with digital inspection reporting. Before sending survey invitations, the survey was tested on an experienced production supervisor working with production data over the last 30 years, resulting in minor modifications. The survey was conducted using SurveyMonkey [68] with 22 questions. Based on the interview findings, the survey respondents were asked to grade to which extent they agreed that digital issue reporting gave benefits such as cost and time savings. Other survey questions assessed the respondents' attitudes towards NLP techniques for improving the issue-reporting quality. The survey questions were organised into the categories “background & roles, “issue reporting”, “challenges”, “opportunities”, and “future features”, inspired by the previously mentioned concept of Future workshops [65].

The full survey organisation, the questions, and the answer types are presented in Paper III.

A minimum requirement for answering the survey was to have performed digital issue reporting in at least one construction project. Therefore, the survey invitation was e-mailed to 495 Dalux Field users, of which 282 reached their intended receiver (non-successful emails were mainly due to outdated email addresses). The response time was set to three weeks, and a reminder was sent after one week, two weeks, and the day before closure. A total of 131 responses were received.

The answers from free-answer questions were analysed by transferring the responses to Miro notes and clustering them into themes.

3.2.4 Data analysis of production data with the KDD method

The data collected from Dalux Field was analysed using data mining. The chosen data mining strategy was the Knowledge Discovery in Databases (KDD) model [69], [70], [71], [72] since it has broad applicability for both academic and industrial purposes [73]. This research used the simplified five-step KDD process described by Yan et al. [69]. The steps are shown in Figure 8.

The first three steps in Figure 8 are presented in this section, whereas the last two are shown in the result section.

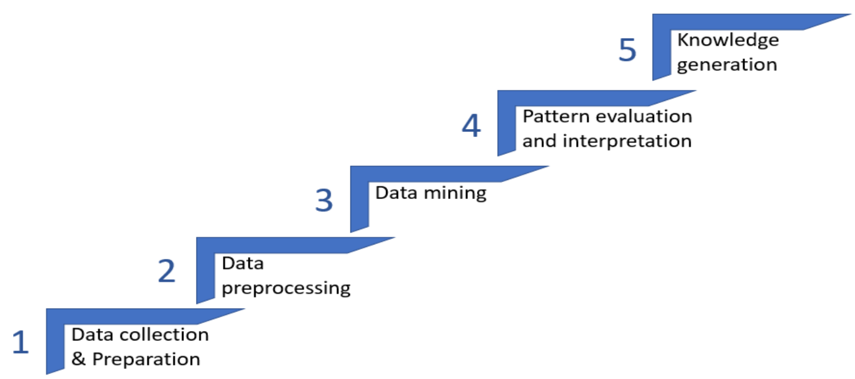

Figure 8. KDD steps performed in the production software data analysis.

3.2.4.1 Data collection and preparation

The dataset described in Section 3.2.1 was reduced by only selecting inspection remarks generated in hospital projects. The choice to focus on hospitals was motivated by the hospital projects’ large number of issues and consistent reporting. The reduced dataset contained a total of 34069 issues.

3.2.4.2 Data preprocessing

After collecting all hospital inspection remarks, the remark title and description were analysed. Since some remarks contained only titles and others had poor titles but long descriptions, the titles and descriptions were concatenated. Then, special characters, numbers and stop words were removed, and all upper cases were turned into lower ones by writing a Python script using the toolkit NLTK (Natural Language Toolkit) [74].

3.2.4.3 Data mining

The data mining and analysis were made in four steps to combine insights given by the large dataset with project-specific information. The steps followed were:

- A: Clustering on the large data set
- B: Topic frequency analysis on the project level
- C: Clustering on project level
- D: Evaluation and interpretation

Step A:
The processed text was vectorized using TF-IDF vectorization [75] and clustered using k-means [76]. K-means is an algorithm that divides the dataset into different clusters, in this case, the inspection remarks, depending on how near they are to each other. The algorithm works by organizing *k* different centroids to different values and then alternating between two different steps until convergence. In one step, each training example is assigned to cluster *I,* where *I* is the nearest centroid. In the other step, each centroid is updated to the mean of all training examples assigned to that cluster [31].

The clustering results in extensive word vectors. Therefore, principal component analysis (PCA) was used to reduce the dimensionality and enable a visual two-dimensional representation of the clusters. The PCA, K-means clustering, and TfidVectorizer were all imported from the toolkit Scikit-Learn for Python [77]. Then, from each cluster, the main keywords were extracted by writing another Python script, and the keywords and their corresponding cluster were plotted using the Seaborn toolkit [78].

Step A generates general insights regarding the main problems discovered during the hospital inspections to summarize all hospital issues.

Step B:
The keywords identified in Step A were used for filtering issue titles for a specific project. The keyword topic frequencies were then plotted along the project production months. Performing Step B allows for comparisons between projects and gives an understanding of when during the production time specific problems are detected. It also provides the possibility to see correlations between topics.

Step C:
The same clustering procedure as in Step A was used in Step C. In addition, the inspection remarks were filtered on titles for the keywords extracted in Step A but clustering on the descriptions. The filtering and clustering were made on a project level to enable comparisons between projects.

Step D:
Key numbers were calculated to evaluate the results and compare projects. Since the analysed projects were of different sizes, dividing the number of issues within a specific topic by the project contract sum enabled a fairer comparison.

4 Results

4.1 Digitalisation and analysis of client requirements: Study A

A systems engineering approach already in the initial requirements review would be necessary for overall successful SE implementation [18], [19]. As a start for the contractor's project requirement decomposition, analysing the client requirements specified in the tendering procurements is essential. According to a Dutch study, the three most common requirement issues are ill-defined client requirements open to multiple interpretations, derived requirements without any design decision, and unnecessarily prescribing a solution [79]. To understand the present content and quality of the client requirements in the Swedish housing market, a pre-study of 22 tendering procurement projects was made.

The results of the pre-study of tendering procurement content are presented in Table 3, showing the most frequently appearing document types, how many tendering procurements they were occurring in, and which format they were delivered in.

Table 3. Presence of document types in tender procurements

Document Type	Presence [%]	Format
Architectural drawings	95	PDF
Technical building description	86	PDF
Room descriptions	82	PDF
Administrative regulations	77	PDF
Fire safety description	77	PDF
Technical description of the ventilation system	68	PDF
Technical description of electricity and tele.	68	PDF
Technical description of plumbing and heating	64	PDF
Geotechnical PM and soil conditions	64	PDF
Landscape planning	59	PDF

Almost all documents in the tendering procurement were in PDF format, and the most frequently appearing document type was architectural drawings, followed by the technical building description. When analysing the five most frequently appearing documents in more detail, the results aligned with Elich et al. [79]. Some of the client requirements were unspecific and could be interpreted differently. At the same time, others were very specific but did not explain why the client chose that detailed specification level. There was also a mix of purely functional requirements and product and component requirements. Some requirements were also contradictive. Some examples of ventilation requirements strongly impacted the choice of material for the structural floor. Those restrictions and contradictions are sometimes challenging to discover since the time to analyse the client requirements is limited, and various documents are often divided and studied by different engineering disciplines.

Despite architectural drawings in PDF format being the most frequent tendering procurement document, the document selected for the requirement analysis automation was the technical building description. The motivation for the choice was the following:

- Architectural PDF drawings are often generated from a BIM model, meaning it is preferred to work directly with the more informative BIM model in data analysis.
- The architectural drawings are a representation of client needs but not necessary requirements.
- Most procurement documents were in PDF text format. Therefore, a text-targeting tool can be easily applied to other procurement documents.

Due to the time restraints for bidding on a tender project, it was assumed that a more automated requirement review process would be helpful for both clients and contractors. An AI work support tool for tendering specialists was developed and evaluated through a workshop (Paper I) and two surveys (Paper II) to explore how the process of analysing the client requirements can be automated and which benefits it can generate in the tendering stage.

4.1.1 AI tool validation

The sensitivity of various text differences could be tested by creating a building description document with simplified text, copying it, and manipulating the text in the copy. Then, both documents were uploaded to the tool, and changes in similarity on the AMA code level were analysed.

If a text under a specific AMA code consisted of a short sentence, the tool became sensitive to misspelt words. In the extreme case, where only one word was written, it was enough to remove one letter to generate a similarity equal to zero since the word couldn't be identified. However, for a large text corpus, some spelling mistakes impacted the results very little.

If a word is not found in the dictionary, the tool ignores it, which becomes an issue if an AMA code consists of a short sentence with a high frequency of construction-specific words. The software in those cases gave a too high similarity since the essential words were omitted. Product names could naturally not be found in the dictionary and were therefore excluded, sometimes leading to overestimated similarities since the critical difference was found in the product name or number.

4.1.2 The usefulness of automatic requirement extraction and analysis

4.1.2.1 Survey results (Paper II)

The pre-workshop survey was sent to 59 specialists, and 38 responses were received, corresponding to an answer frequency of 64%. The distribution of responses among the specialist disciplines is presented in Table 4.

The post-workshop survey was sent only to persons who answered the pre-demo survey and attended the AI-tool demonstration, which was a total of 38 persons and 25 responses were received, corresponding to an answer frequency of 66%.

Table 4. The respondents' specialisations

Specialist category	Percental distribution [%]
Geotechnical engineers	8
Structural engineers	5
Energy/LCA/Sustainability engineers	24
Building service engineers	16
Cost estimators	47

Most respondents in the two surveys investigating the perceived usefulness of the AI tender tool found the tool's text extraction and benchmarking functions helpful, and the ease of implementation was considered high.

The subthemes found among the open answers in both surveys are presented in Figure 9. The percentages displayed are the frequency of responses belonging to each subtheme.

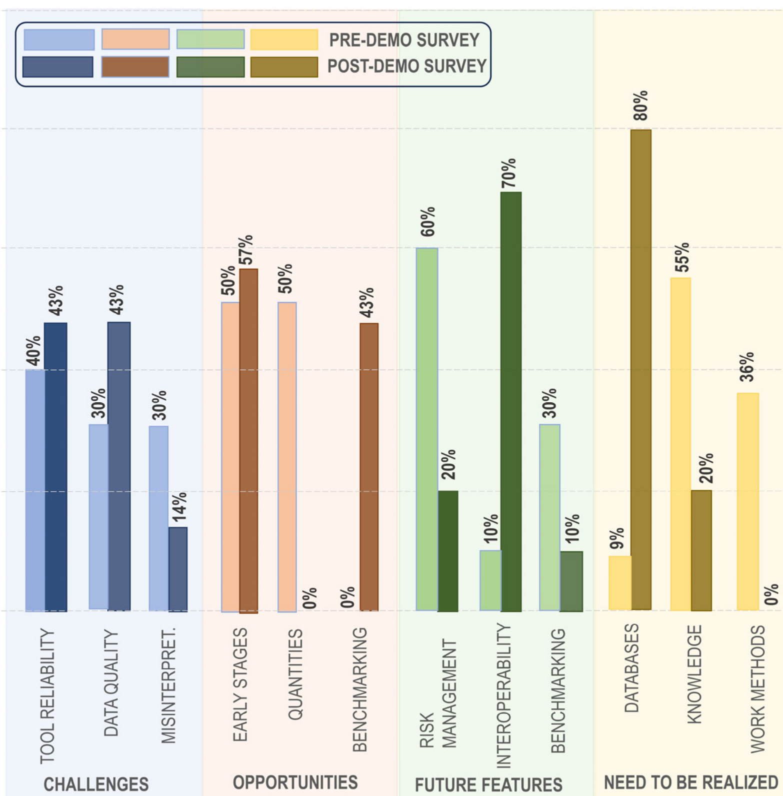

Figure 9. Answers to open questions in pre-demo and post-demo surveys. The bars represent the distribution of sub-theme responses within each main category.

Some differences between the two survey answers were:

- Fewer respondents found misinterpretation risks a challenge in the second survey.
- Before the tool demonstration, there was a high belief that the tool should help quantify materials. Since the tool did not have such a feature, this opportunity category dropped to zero in the second survey.
- Benchmarking was considered an opportunity in the second survey.

- The desire to integrate the tool into existing software increased from 10% to 70%.
- The need for creating databases was considered very high in the second survey.
- After watching the tool demonstration, the respondents did not see any need to change the present work method before adopting such a tool.

Risk management, interoperability, and benchmarking were subthemes within desired future features. Within risk management, the ability to use the tool for rapidly scanning all requirements for data-informed bid/no-bid decisions was often mentioned. In addition, more automated analysis of many client requirements means less need for time investments before reaching the bid/no-bid decision and a decreased risk of investing time in unpaid work.

The most common response in the subtheme "benchmarking" within the category "Desired future features" was creating discipline-specific templates and making the tool autofill the extracted requirement into those templates. One example could be extracting and summarising requirements impacting energy calculations, such as u-values, heating systems, and floor areas.

The surveys identified the need for some actions before such an AI tool can be implemented. The most frequent answers mentioned the need for knowledge increase among potential users and the need for creating and maintaining accurate databases.

More results from the two surveys can be found in Paper II.

4.1.2.2 Workshop results (Paper I)

The comments gathered during the workshop were further analysed and clustered into sub-themes. Figure 10 presents the main categories and sub-themes identified.

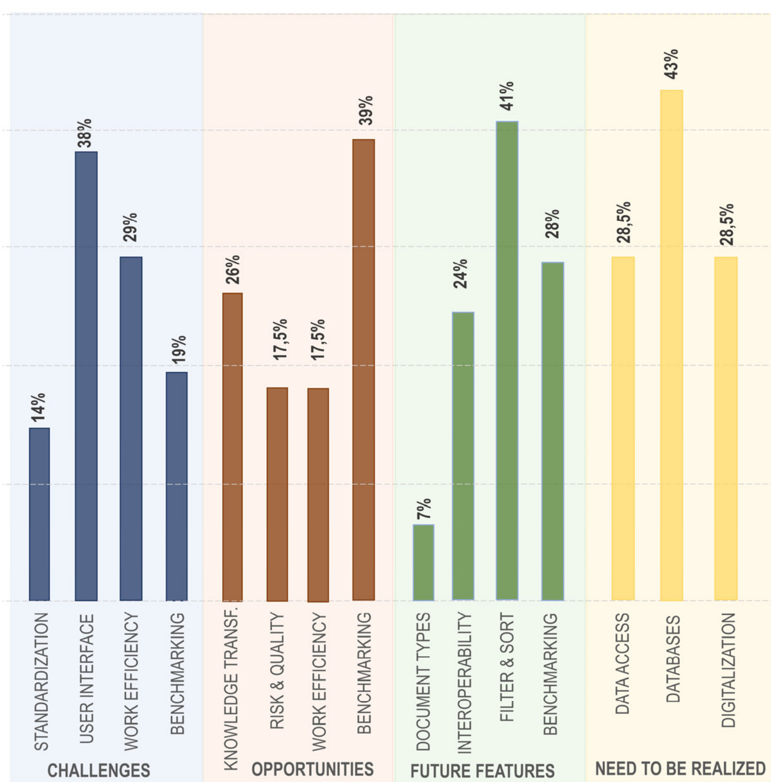

Figure 10. Workshop results presented as main categories and sub-themes. The bars represent the distribution of sub-theme responses within each main category.

The largest opportunity identified in the workshop was for benchmarking purposes. Many participants perceived the benefits of comparing new projects with previous ones based on categorising parameters. For instance, some specialists mentioned the possibility of benchmarking contractual conditions inter-projects, while others suggested that the tool could help keep track of problematic technical solutions in perspective to aftermarket performance.

Most comments in the "Future Features" category were suggestions for filtering and sorting information considering varied parameters. For instance, many participants wanted to find projects with similar customer requirements and the same structural system, given an extensive database of completed 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 for risk identification.

Among actions needed before implementation, a few crucial concerns were introduced, such as digitising data from historical projects, creating databases, and allowing proper access. Another concern was the need to establish correct, relevant, and comparable information.

More results from the workshop can be found in Paper I.

4.1.2.3 Comparison of survey and workshop results

Regarding challenges, there was a difference in answer focus between the surveys and the workshop. The survey results showed concerns regarding the tool's reliability and data quality. In contrast, the workshop focused on the user interface and the risk of adding another task to an already work-intensive project phase.

Among opportunities, benchmarking was a significant category in both the surveys and the workshop. However, the survey results found early stages, such as the tendering phase, a large opportunity area for the tool implementation, but the workshop results target more general knowledge transfer from previous to new projects.

As a future feature, the most frequent workshop answers concerned various filtering and sorting possibilities. In the surveys, particularly the post-demo survey, the focus was instead interoperability with existing software.

Creating and maintaining databases was identified as important before tool implementation in both surveys and the workshop. The workshop insights also mention digitalisation and data access as crucial.

4.2 Production data for verification & validation: Study B

In the Swedish construction industry, the verification of the fulfilment of requirements is made against the calculations, drawings, or BIM model. Many verifications are made using self-inspection, meaning that the designer who has performed a specific task or drawing makes a check so it's fulfilling the requirements. The checklists usually do not only include legal and client requirements but also production aspects.

Validation within the construction industry is primarily made through checklists and inspections. In the Swedish construction industry, the use and purpose of the inspections are defined in AB04 (Bid-build contracts) and ABT06 (Design-bid-build contracts), which are two common contractual frameworks [80]. There are six common inspection types used in the Swedish construction industry [81], [82], and a summary of them is given in Table 5.

Table 5. Inspection types, purposes and when the inspection is performed.

Inspection	Purpose	When
Final stage inspection	Verifying that the performed works fulfil the agreed contract.	In the final stage of a project/project phase
Pre-inspection	Verifying initial project/site conditions or	Before project starts
	Inspection of building parts that will be invisible during the final inspection.	Anytime
After inspection	Verifying if the contractor has addressed previously discovered issues sufficiently.	After a final stage inspection or pre-inspection
Warranty inspection	Discover possible inadequacies that the warranty shall cover.	Before the end of the warranty period
Special inspection	Discover more severe problems with a specific building part that might not have been noted during the final inspection.	After the final stage inspection
Over-inspection	A new inspection by a different inspector if the client and/or contractor are unhappy with the outcome of the final inspection.	Within two weeks of receiving the final inspection report

4.2.1 Digitalisation of inspection data

Traditionally, data collection in the construction industry has been manual [83]. The remarks discovered during field inspections have been noted on handwritten papers and sometimes later transferred into Word and PDF documents. However, McCullouch & Gunn [84] tried to digitalise field data regarding timekeeping and material quantities. Their study found potential time savings due to less paperwork and downstream benefits with more straightforward data processing if other management software further processed the acquired data. Cox et al. explored the potential of digitalising inspection forms and predicted digitalisation would be the key to data quality improvement [85].

Software for digitally reporting production and inspection issues has gained popularity during the last five years. Today, construction workers have individual mobile devices and can access and store data cloud-based. The more straightforward data accessibility has increased the interest in and the use of issue-reporting software. Some of the previously identified challenges with a digital collection of field data [84], [85], [86], [87] have now been overcome due to higher digital knowledge and better devices.

The study presented in paper III was conducted to investigate the state-of-the-art with present digital inspection data reporting. The first part of the study presented in this section addressed the project and team member incentives with digital work methods and the current data quality.

Data from a total of 34 projects were analysed. The projects' building category is presented in Table 6. The most common issue type reported was remarks generated during pre-inspection, representing almost 46% of all registered issues. All issue types and their frequencies are presented in Table 7.

Table 6. Number of projects of each building category

Building Category	Number of projects
Apartments	8
Hospital	7
School	7
Office	5
Hotel	2
Car Gallery	1
Parking	1
Police station	1
Swim hall	1
Train station	1
Total	**34**

Table 7. Issue types, frequencies and their share of the total number of cases.

Issue type	Number of issues	Share [%]
Pre-inspection	43806	45,9
Inspections	17967	18,8
Deviations	9458	9,9
Control	8782	9,2
Observations	7034	7,3
Final inspection	2190	2,3
Safety issue	2188	2,3
Inventory	1204	1,3
As-built information	225	0,2
Warranty, reclamations & after-sales	184	0,2
Self-inspection	145	0,2
After inspection	97	1,5
Changes & additional work	70	1,5
Other issues	2003	2,1
Total:	**95353**	**100**

4.2.1.1 Data quality

To understand the quality of the provided data, 19 features, their insertion methods and estimated data quality were studied, and a summary is given in Table 8.

Table 8. Features, their data quality, and insertion method.

Feature [Name]	**Data quality** [High, average, low]	**Field mandatory** [Yes/No]	**Insertion Method** [Autogenerated/ manual/droplist]
Project name	High	Yes	Manual input
Project ID	High	Yes	Autogenerated
Project number	High	Yes	Autogenerated
Creation date	High	Yes	Autogenerated
Issue ID	High	Yes	Autogenerated
Issue Number	High	Yes	Autogenerated
Title	Low	Yes	Manual input
Description	Low	No	Manual input
Discipline	Low	No	Droplist & manual
Inspection Type	Average	Yes	Droplist & manual
Object name	Average	No	Autogenerated
Company name	High	Yes	Manual
Assigned to Company name	High	No	Droplist
Assigned to Company ID	High	No	Autogenerated
Assigned to user	Average	No	Droplist
Personal user data	High	Yes	Manual
User ID	High	Yes	Autogenerated
Name	Low	No	Manual

Autogenerated or predefined data harbour a higher consistency and quality. Project data is entered manually at the setup of a new project by a project leader or BIM coordinator. Also, personal user data, like email, first name, and family name, are entered while registering a new user. On the contrary, data manually inserted by project members, like title and description, are relatively low quality. However, there is a large dispersion between the issues. For example, some titles and descriptions are detailed, while others have general titles, and the description field might be blank.

The field "discipline" is pre-defined in terms of a drop list, but users can also add disciplines they find missing. The interpretation of what data shall be inserted differs between users and even more between projects. For example, some use the technical discipline to which the issue relates, such as plumbing, structural systems, ventilation, etc. Others use which part of the project the issue concerns, such as Building A, Staircase C, etc. Others specify which part of the building, such as wall, ceiling, etc., the issue concerns. Another frequent use of "discipline" is to establish from who to whom the issue is sent, for example, "Inspector to Ventilation" or "Contractor to Painter."

"Object name" has an estimated average data quality. An object name is generated if an issue is locked to a BIM object. However, the field is left blank if the issue is not attached to the BIM object, which is the primary case.

4.2.1.2 Requirements traceability

When analysing the dataset, a general assessment of the requirements traceability was made. Most issues were reported without referring to which requirement they were corresponding to. Since the data in the field "discipline" was of low quality and left room for interpretation, it was difficult to categorise the production problems.

During the interviews, some projects showed a refined digital work process for reporting checklists and self-inspections. Checklists and control documents were digitised in those projects, and all reporting and signing were made digitally. If problems were discovered, the issues were documented with a photograph. The process provides a significant source of information for improving work preparations and future knowledge transfer. However, most checklists and self-controls also lacked requirements traceability. When asked about traceability improvements, the interviewees thought it would be possible but harbour some labour.

4.2.1.3 Incentives with digital issue reporting

The survey respondents were asked about the main benefits for themselves and the project. The two questions were asked as open-answer questions, and the answers could be divided into six categories. The differences between perceived individual and project benefits are shown in Figure 11.

One large benefit of digital inspection reporting for individual project members and the projects was the general facilitation of the inspections. When digitalised, administration got easier and faster, and the team leader or supervisor could easily forward and assign remarks to team members. Adding photographs and coordinates to the inspection issue clarified the extent and exact location.

Increased use of BIM models in production was another significant benefit in the survey answers. Instead of using the BIM model only for locating and understanding issues, more site staff discovered the advantages of BIM and started to use the 3D model for preparing and planning their work. Always finding updated BIM models and corresponding 2D drawings in one place, with accessibility from mobile phones or tablets, was an often-mentioned benefit. Lastly, time-saving and increased control were considered essential benefits. Reporting issues digitally was considered faster than writing on paper and reduced the manual paperwork. Directly adding issues to the database made them immediately available for project members, making the project save time by not having to wait for an inspection report. Time savings among the production supervisors were also found in not needing to walk around physically showing and explaining various remarks. The issues could instead be assigned to specific project members, allowing them to calmly read through and analyse before starting the adjustment works.

After the free answer questions about benefits, the survey respondents were asked to rate to what extent they agreed that digital issue reporting added value in general, reduced costs, and saved time. As seen in Figure 12, 90% totally or partially agreed to digital issue reporting adding value to the project. More than 64% partially or completely agreed that digital issue reporting reduced costs, and 80% partially or completely agreed that it also saved project time.

More results from the survey and the interviews in Study B can be found in Paper III.

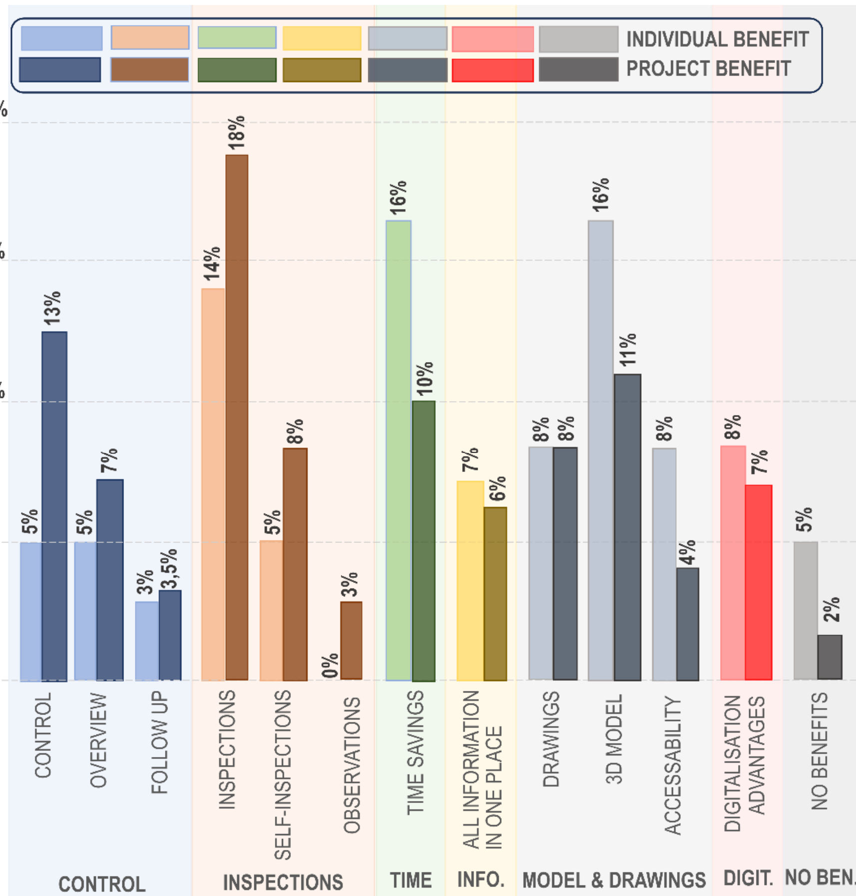

Figure 11. Main and subcategories for most significant individual and project benefit. The bars represent the distribution of responses within individual and project benefits.

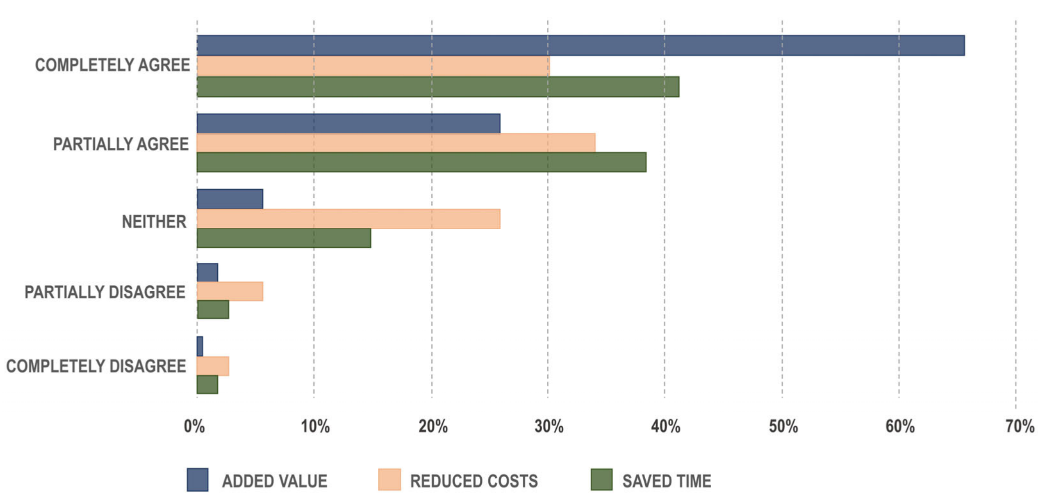

Figure 12. Answers to questions: To what extent do you agree that digital issue reporting: A: Added value to the project? B: Reduced project costs? C: Saved project time?

4.3 Generating knowledge from digital inspection data: Study B

Lundkvist & Vennström [88] investigated the possibility of enhanced learning from inspection data through a survey and found that more than 80% of the respondents considered inspection data a valuable source of knowledge. Still, over 50% of the companies did not use the data collected. Their study also showed that even if inspection data is stored, and sometimes even digitally, the information is rarely shared between projects.

Therefore, Study B also explored how AI technology can facilitate knowledge generation from digital inspection data. Since the most interesting qualitative data, consisting of unstructured text, was found in titles and descriptions, clustering techniques were chosen for exploring knowledge generation possibilities. The clustering was conducted on hospital project data from the previous dataset, resulting in 34069 production issues.

4.3.1 Step A: Clustering on the large dataset

The result from the clustering on the large hospital dataset is presented in Figure 13. Four main clusters were identified by a trial-and-error approach, i.e. changing the number of clusters until a sufficient detail level in the keywords was achieved. The red cluster looks partly integrated with the others due to the choice of doing a two-dimensional PCA plot. However, looking at the cluster in 3D, there is a clear distinction between all clusters.

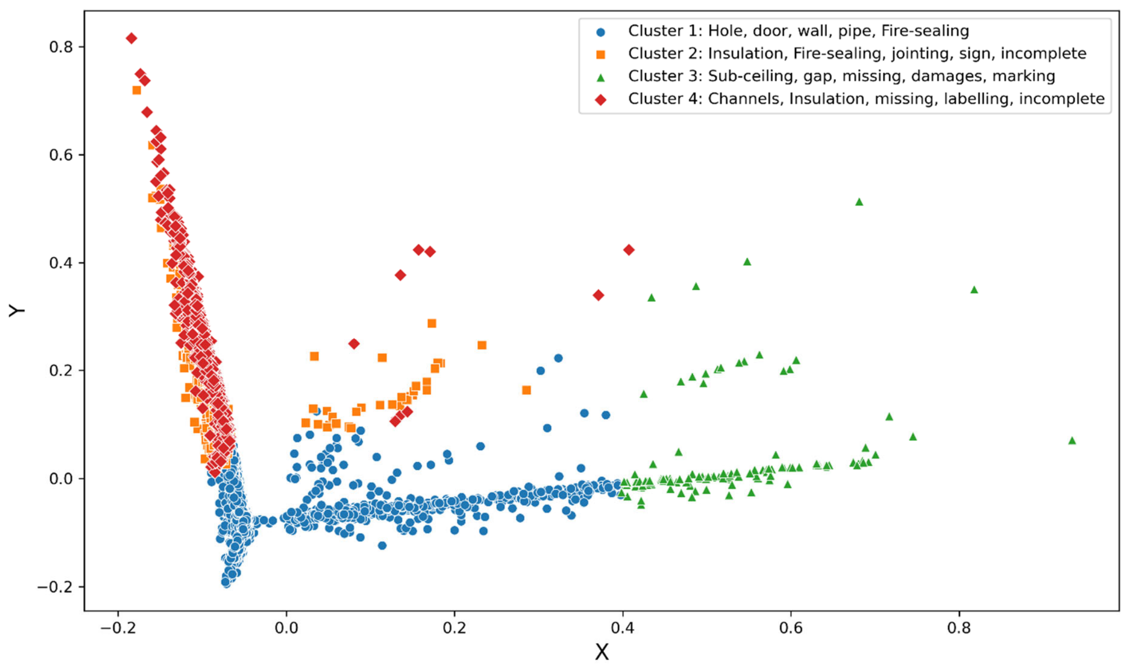

Figure 13. Main clusters in the large dataset. The axes X and Y are representations of the principal components. Each colour represents a cluster, and each dot is an inspection remark belonging to that cluster.

The most common keywords for each cluster are presented at the top right in Figure 13. The keywords for Cluster 1 indicate that the most significant problem category is fire-sealing around pipes and holes through walls or around doors. For Cluster 3, with green symbols, the keywords indicate problems with missing or incomplete sub-ceiling. Even though the keywords are extracted automatically, it requires some domain knowledge and familiarity with the dataset to interpret them.

4.3.2 Step B: Topic frequency analysis on the project level

Figure 14 presents the topic frequency of the keywords belonging to the blue cluster for two different hospitals. Hospital 1 had more remarks regarding fire-sealing around doors, while Hospital 2 had more pipe-related fire-sealing issues. The curves indicate how the topic frequencies varied during the project's progress. The results from Step B help find patterns and differences between projects and can serve as input for further investigations regarding project performance.

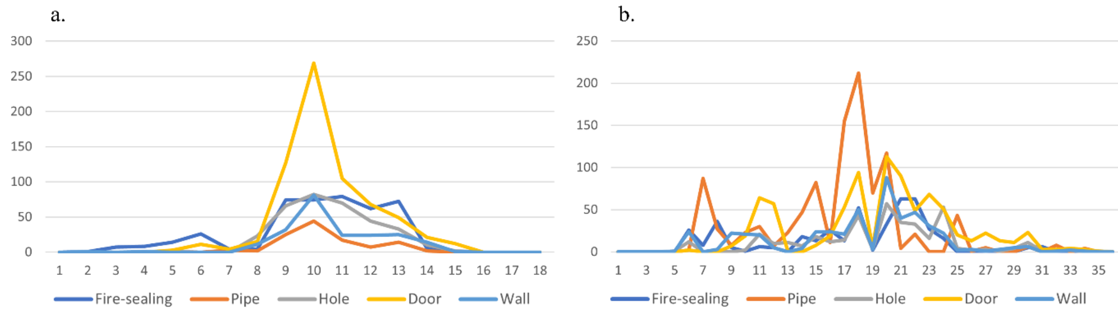

Figure 14. (a) Topic frequencies for keywords from the blue cluster for hospital 1. (b) Topic frequencies for keywords from the blue cluster for hospital 2. The x-axis shows the number of production months, and the y-axis indicates the number of inspection remarks with a specific topic reported that month.

4.3.3 Step C: Clustering on project level

After filtering issues using the keywords from the first clustering, a second round of project-specific clustering was made using the inspection remark descriptions. Figure 15 presents the PCA plot for clustering on fire-sealing and proofing in Hospital 1. The extracted keywords were "fire-sealing, fire-sleave, missing, not performed" for Cluster 1, "insulation, missing, fire-sealing, labelling" for Cluster 2, and "cables, walls, missing, needs" for Cluster 3. The keywords led to the problem category interpretations: "Fire sealing or fire sleeves are missing", "Insulation or sealing is missing labelling", and "Cable penetrations through walls are missing fire sealing".

Figure 16 shows the PCA plot for clustering on insulation remarks in Hospital 2. For Cluster 1, the extracted keywords were "damaged, incomplete, missing, insulation", indicating general issues where insulation is missing, damaged or incomplete. For Cluster 2, the extracted keywords were "sound insulation, fire-insulation, labelling, missing", showing problems with both fire insulation and sound insulation missing proper labelling. For Cluster 3, the keywords were "condensation insulation, earthing, missing, restored", indicating problems arising following the earthing process, highlighting the need to either restore or address the absence of condensation insulation.

The clustering results from Step C give keywords specific enough to understand which fire sealing and insulation issues are in the dataset. Using this clustering technique, an organisation can compare which subcategories of remarks can be found within a particular issue topic. Comparing projects can be made to find good examples or to spot anomalies. The information gained can further support an organisation in improving quality and processes to address some of the problems detected.

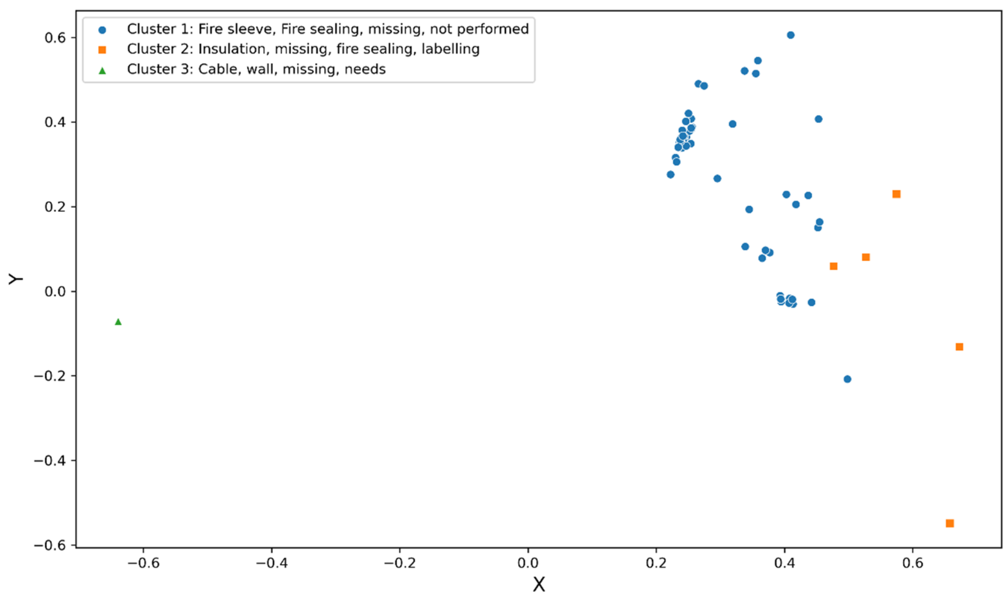

Figure 15. PCA plot for clustering on inspection remarks concerning fire sealing and proofing for Hospital 1. The axes X and Y are representations of the principal components.

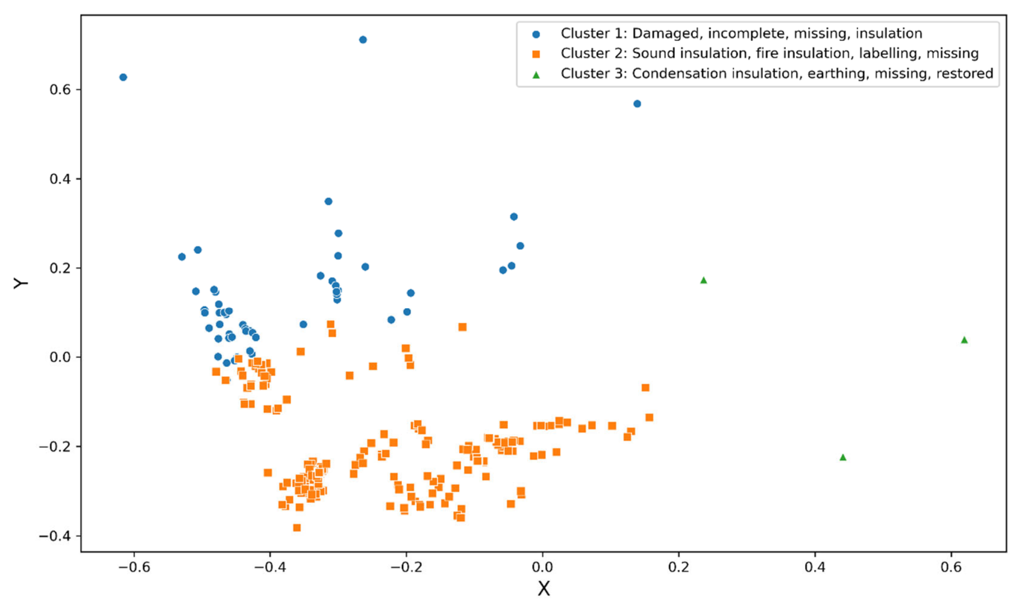

Figure 16. PCA plot for clustering on inspection remarks concerning insulation in Hospital 2. The axes X and Y are representations of the principal components.

4.3.4 Step D: Evaluation and interpretations

Looking at key numbers helps evaluate the results further and compare projects. For example, in this research project, the number of remarks was compared to the estimated contract price, but another option would have been to compare with the total building area. Since a larger project likely will have more inspection remarks than a small project, dividing the number of issues within a specific topic by the project price or total floor area gives more comparable numbers. Table 9 presents the issue intensity per million Swedish crones. The percentages within brackets are how large part of the total number of project issues the specific topic represents.

Table 9. Key number comparison of hospital issues.

	Hospital 1	Hospital 2
Contract price [MSEK]	625	885
Total number of remarks	8655	19369
Fire sealing remarks per [MSEK]	0,69 (4,9%)	0,49 (2,3%)
Sub-ceiling remarks per [MSEK]	0,24 (1,8%)	1,4 (6,6%)
Insulation remarks per [MSEK]	0 (0%)	1,6 (7,2%)

By comparing key numbers, significant differences between projects can be detected. In this example, the organisation should investigate why insulation remarks represent more than 7% of the issues in Hospital 2 but almost zero in Hospital 1. The project team in Hospital 1 might have had a more effective process or method for avoiding insulation problems.

5 Discussion

5.1 Requirements analysis

The AI tool developed in this research project enables automatic extraction and statistical analysis of client and regulatory requirements. Overall, the tool performance was good but can be further improved by training on a construction-specific dictionary or applying POS techniques, which has proven useful for domain-specific text in the study of Xue et al. [56].

The AI tool was developed in the spring of 2021, and as a vectorisation model, Word2Vec was chosen and implemented. Word2Vec uses static word embeddings. Since then, the usage of transformer models, such as BERT and GPT, has increased. The transformer models use contextual word embeddings, meaning that a vector representation of a word depends on its relationships with other words in a sentence. Replacing Word2Vec with a transformer model could improve the tool's performance, particularly if combined with Named Entity Recognition for frequent construction entities.

The tool was designed to extract text and categorize them into AMA codes. The AMA structure was chosen since most technical building descriptions follow the AMA structure, facilitating text extraction and similarity analysis. However, the surveys and workshop found that most tendering specialists prefer the information sorted on building parts. Most AMA codes relate to a specific building part. Therefore, it would be possible to further sort them into categories, such as structural framework, foundation, exterior walls, windows, etc. Such sorting may also facilitate the creation of specialist-specific templates identified as a desired future feature during the workshop.

Since the developed AI tool was demonstrated to introduce the survey and workshop participants to the possibilities of NLP techniques, the second survey may have biased answers. This is likely the explanation for identifying more benchmarking opportunities and the drop in material quantity possibilities. However, the method chosen is justified as it enabled the evaluation of technology previously unknown to the participants.

Independently of the choice of the large language model, when applying them in high-stake contexts such as requirement analysis, contract evaluations or juridical documents, it must be considered that no model is perfect. Phenomenons such as hallucinations, when LLMs produce responses that do not accurately reflect the given context, are not supported by evidence, or deviate from the expected behaviour based on their training data, need to be considered and handled. Changes in model performances, known as model drift, must be accounted for when building any application on a machine-learning model. Also, the mathematical similarity calculated by the model might differ from the human perception of the similarity, particularly when comparing large text chunks or complete documents.

The same technology and process used in this research project for extracting and analysing client requirements can be used for other purposes. The tool used as a base for the study presented in Paper I and II extracted text from technical building descriptions and compared them to a material and performance framework. Another possible application of the same technology would be to perform the same extraction and similarity computation on the general regulation document and compare it with AMA AF, a framework for the formation of general regulations. Such a comparison would enable fast identification of contract risks and juridical aspects needing particular attention.

5.2 Knowledge transfers

Production data, such as inspection issues studied in this research project, can be input into the early phases of construction projects. This study shows that digital production issues reporting gives project benefits such as time savings, cost savings and general control improvements, an essential foundation for continuous usage and data supply over time. The generated data is analysed to a small extent in the current projects, but new projects could benefit from analysing data from several similar projects. The production data can facilitate decision-making regarding the choice of a subcontractor, production method or risk management.

The data can also serve as a baseline for quality improvement. For example, suppose the present issue frequency for a specific problem and building type is 0.3 issues per m^2. In that case, quality improvement activities can be evaluated using that number as a baseline, enabling long-term progress monitoring when performed continuously over time.

To facilitate the pre-processing, it is necessary to improve the general data quality, particularly on qualitative data like titles and descriptions. Today, the field "description" can be left blank, leading to many issues missing an explanation. Moreover, if their title is also poorly chosen, it becomes almost impossible to understand what the issue concerns. It is suggested to improve the data quality by addressing the data input and pre-processing automatisation. Sentence autocompletion was considered useful among the survey respondents in Study B, indicating that introducing such a feature would help both the issue reporter and the later data analysis. An example is when an issue reporter starts writing the title 'Painting', the software can automatically suggest autocompletion like 'Painting damage', 'Defective painting,' or 'Missing painting.' This can help the reporter be more specific in the choice of title and make the data analysis more accurate.

Another natural language processing technique for data improvement would be topic identification. When a project member clicks on a BIM or drawing object, topic identification is used for presenting the most common issue types connected to the chosen object. When asked if such a feature would be helpful for the individual issue reporter, more than 60 % of the respondents perceived it helpful.

In this research project, unsupervised learning by using clustering techniques was used. The suggested method gave insights into the dataset's general issue categorisation and which subcategories of problems were found within the main clusters. The method is useful for quickly generating organisational insights and comparing projects. The method could be further elaborated by using more advanced language models for vectorisation. If, in the future, the category "discipline" has a higher and more consistent quality, the clustering quality could be enhanced by using the discipline label as side-information, as Aggarwal et al. [89] suggested.

Using insights generated from the clustering can serve as a knowledge base when updating work preparation instructions or deciding which issues to monitor over time on an organisational level.

The issue reporting frequency analysis presented in Paper III shows inconsistencies in the issue reporting between the projects. The survey and interview answers show a high belief that having more standardised and continuous issue reporting, starting earlier in the projects, is possible. Such an implementation could enable project progress monitoring by analysing issue frequencies and complementing visual AI techniques rating the completion rate.

The survey results in Study B show a general optimism towards digital inspection reporting and identified general benefits as well as time and cost savings. Additionally, the possibility of locating an issue in a 3D model did not only remove uncertainties about where a problem was found, but a side effect was a widespread usage of the 3D model as a work support among the blue collars. Ma et al. [90] proposed an approach for a more efficient quality management process within construction projects. The first part of their process suggests localising the issues in the BIM model, which the studied inspection reporting software enables. The second part of their process suggests using the BIM model to generate inspection tasks. Instead of using only the BIM model, incorporating client requirements for developing inspection tasks and checklists could improve overall quality management. Using clustering methods to gain knowledge regarding frequently occurring or high-risk issues and using the knowledge for further elaborate checklists can proactively reduce risks in new projects.

The method used in the requirement extraction in Study A enables storing requirements in a database and comparing new project requirements with previous projects. By comparing the overall document similarities, it can serve as a future tool for document or project retrieval. Knowledge and data generated at earlier tendering projects can then be used in new projects, allowing insights also from data generated in projects where the contractor lost the bidding, which is currently limited.

5.3 Systems engineering

To implement an AI-supported systems engineering approach in construction projects, linking the verifications and validations analysed in Study B with the requirements extraction and analysis in Study A would be necessary. Even though various kinds of production problems were reported using the production software, no apparent link to which requirement they verified was found. Other research has also highlighted the requirement traceability problem, and some initial attempts to automate the generation of project-specific control plans have been made [23]. Linking client and regulatory requirements to verifications, such as controls, inspections and checklists, would facilitate future knowledge transfer and enable statistical analysis of production problems. Even though the effort required to link requirements with verifications can be challenging and extensive, the mapping process can be automated once the connections are established, and data from both requirements decomposition and verifications and validation are available digitally. Various AI techniques may serve as valuable tools to facilitate automation. A suggestion for how AI can facilitate a systems engineering methodology implementation in the construction industry is presented in Figure 17.

The first step in the process means an automatic extraction of client requirements using NLP techniques. The next step would be to label the requirements and map them with proper verification and validation methods. In step three, requirements missing proper verifications and validations and needing attention can be identified, and the requirement risk evaluated. Step four will be a part of the production preparation, including an automated generation of checklists and control plans based on the requirement analysis. The fifth and last process step means performing and storing verification and validation data digitally, allowing for later validation of the requirement fulfilment. Adopting the process, supported by digital and AI tools, would be a significant step towards systematic requirements management following the systems engineering philosophy.

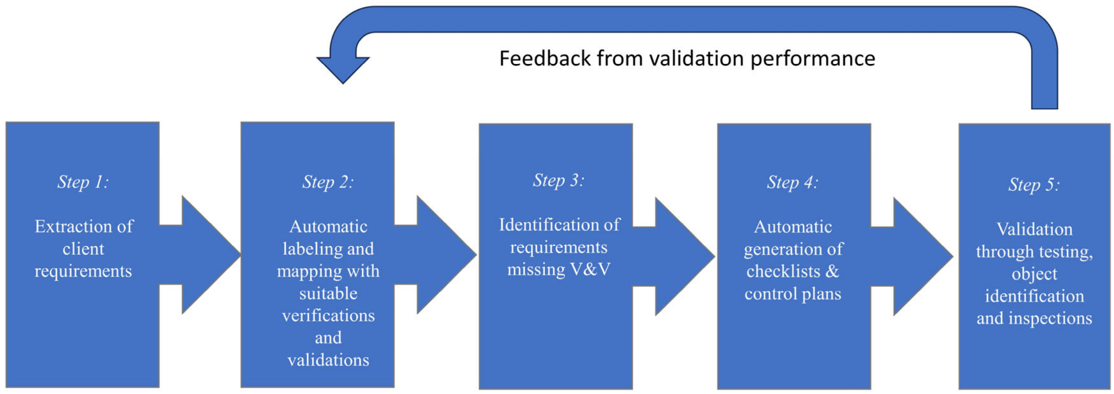

Figure 17. A suggested process for AI-supported systems engineering approach in construction projects.

An automated process may also help improve risk management, an essential part of the system engineering approach. Risk management consists of two parts: risk assessment and risk mitigation [9]. Regarding the risk assessment, access to data from completed projects facilitates the risk identification and judgement of the risk magnitude. It can also help evaluate requirements risks in new tendering projects by identifying requirements missing proper verification and validation methods. Regarding risk mitigation, monitoring verification and validation characteristics can give insights into whether a requirement is fulfilled or not and with which margins. Such knowledge is essential in projects facing new requirements, like stricter CO_2e emission levels or demands for building with reused material. The data may also be essential in decision-making regarding methods and actions to eliminate or reduce project risks.

6 Conclusions

The purpose of this research project was to investigate how artificial intelligence can facilitate circular information flows from production to new tendering projects. The first study explored methods for automatic requirement extraction and analysis using natural language processing techniques and evaluated its usability through surveys and a workshop. The second study examined the current state of the art in digital production issues reporting, explored the benefits of digital issue reporting for projects and individuals by a survey, and suggested a possible method using unsupervised learning for turning production data into organisational knowledge.

RQ1: How can client requirements in the tendering phase be digitalised and analysed in a more automated way?

The research presented in Paper I and II shows that natural language processing can serve as a helpful tool for automating the extraction and analysis of client requirements in tendering projects. Since the number of requirements in a typical construction project is large, digitalising and using artificial intelligence for data extraction and analysis can facilitate requirement management.

RQ2: How can production data be used in new projects?

Production data, such as inspection issues studied in this research project, may serve as input into new projects. The production data can facilitate decision-making regarding the choice of a subcontractor, production method or risk management. Production data can also be essential in monitoring and evaluating quality-improving activities.

RQ3: How can artificial intelligence be used to facilitate knowledge transfer?

Using clustering techniques, such as k-means explored in this research project, can enable knowledge generation from production to new projects. The method suggested and explored combines clustering on the organisation and project level, allowing the detection of quality flaw categories and comparing those categories between projects to identify trends.

7 Future work

A possible future study would explore the possibility of applying AI in the concept explorations phase. Concept exploration is an important early phase of project development in systems engineering. Kossiakoff et al. [9] describe the concept exploration steps as follows:

1. Start with the existing system as a baseline
2. Partition the system into its major subsystems
3. Postulate alternatives that replace one or more of the essential subsystems
4. Vary the chosen subsystem singularly or in combination
5. Consider modified architecture
6. Continue until you have a total of four to six meaningful alternatives

Since the concept exploration phase is time-consuming and usually has limited resources, new methods can benefit a more automated process. One approach showing considerable potential for this kind of multicriteria optimisation problem is Genetic Algorithms (GA) [91]. Genetic algorithms are a kind of evolutionary algorithm first introduced by Holland in 1975 [92]. The method is based on the principles of natural selection, where a population undergoes a gradual change. Applying GA in exploring possible and suitable structural systems can be one way to automate the concept exploration. Translating the concept exploration steps into a GA sequence could be as follows:

1. Start with the existing system as a baseline.
   Select an initial parent population based on commonly used conceptual building design.
2. Partition the system into its major subsystems.
   Define the design variables (materials, loads, building dimension, foundation system, etc.)
3. Postulate alternatives that replace one or more of the essential subsystems.
   Evaluate the parent population by measuring the fitness level (costs, CO_2e emissions)
4. Vary the chosen subsystem singularly or in combination.
   Take the fittest design solutions and use them for making a crossover generating new offspring solution (child populations).
5. Consider modified architecture.
   Insert a mutation to the design values to enable non-existing features.
6. Continue until you have a total of four to six meaningful alternatives.
   Define determination criteria, for example, a fixed number of generations. Select the most fit populations and present possible conceptual design solutions to be evaluated by the project team.

The suggested process is visualised in Figure 18.

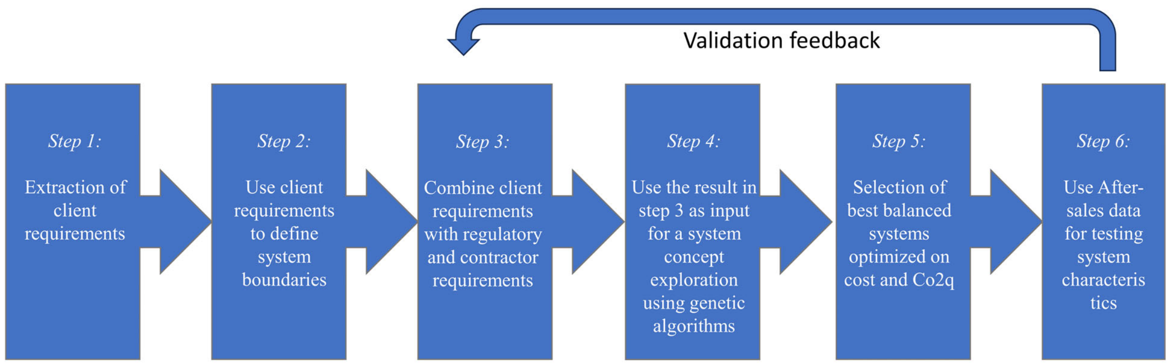

Figure 18. A suggested process for AI-supported concept exploration in construction projects.

The concept exploration can also be adapted to include buildability aspects by allowing to optimise the designed solution for minimising production problems, such as the production issues in Study B. By using data from completed projects linked to structural system choices or structural members, the number of future production problems for the various structural system choices can be predicted and used for risk estimations.

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