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Error Prediction in Industrialized Construction:

A Framework for AI-Powered Error Prediction in the On-Site phase of IHB

Master's thesis in Design and Construction Project Management

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MASTER’S THESIS ACEX30

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ABSTRACT

The construction sector faces notable productivity challenges, as it is known for having one of the lowest productivity levels compared to other industries. Industrialized House Building (IHB) has emerged as a solution for low productivity. However, the sector still faces productivity challenges as delays and cost overruns still exist, mainly due to errors and variations in IHB projects, especially in the on-site stage. To address the challenge of errors emerging in on-site IHB projects, this study aims to investigate the possibility of implementing AI tools for error prediction to mitigate errors in the on-site stage of IHB projects. The study employs an abductive approach through qualitative data collected from a literature review, site visits, interviews, and inspection report analysis in a thematic approach. The study identifies common errors and their impacts, emphasizing the importance of early intervention and predictive technologies in mitigating errors. Key findings reveal that AI can be employed for error prediction, enhancing resource allocation and planning, and minimizing projects' rework. The study proposes a conceptual framework for an AI error prediction tool in the on-site stage of IHB projects to assist project managers in the decision-making process. This study contributes to IHB's error management practices, bridging the gap between the on-site stage of IHB and AI, and serving as a roadmap for IHB companies to implement AI tools effectively. Finally, the research highlights the necessity of robust data management practices and continuous improvement to leverage AI's potential in the IHB project.

Key words: artificial intelligence, machine learning, error prediction, defects, Industrialized House Building, on-site construction, resource optimization, continuous improvement, construction management, prefabrication.

Felprediktion inom industrialiserat byggande:

Ett ramverk för AI-driven felprediktion i byggarbetsfasen av industriellt husbyggande

AHMAD BURQAN

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SAMMANFATTNING

Byggsektorn står inför betydande produktivitetsutmaningar och är känd för att ha en av de lägsta produktivitetsnivåerna jämfört med andra industrier. Industrialiserat husbyggande (IHB) har framkommit som en lösning för låg produktivitet. Dock står sektorn fortfarande inför produktivitetsutmaningar då förseningar och kostnadsöverdrag fortfarande existerar, främst på grund av fel och variationer i IHB-projekt, särskilt i produktionsfasen. För att hantera utmaningen med fel som uppstår i produktionsfasen av IHB-projekt syftar denna studie till att undersöka möjligheten att implementera AI-verktyg för felprediktion för att minska fel i produktionsfasen av IHB-projekt. Studien använder en abduktiv metod genom kvalitativa data som samlats in från en litteraturöversikt, platsbesök, intervjuer och analys av besiktningsrapporter på ett tematiskt sätt. Studien identifierar vanliga fel och deras påverkan, och betonar vikten av tidiga ingripanden och prediktiva teknologier för att minska fel. Viktiga fynd avslöjar att AI kan användas för felprediktion, vilket förbättrar resursallokering och planering samt minimerar projektens omarbetning. Studien föreslår ett konceptuellt ramverk för ett AI-felprediktionsverktyg i produktionsfasen av IHB-projekt för att hjälpa projektledarna i beslutsfattandeprocessen. Studien bidrar till IHB felhanteringspraxis, överbryggar gapet mellan produktionsfasen av IHB och AI och fungerar som en plan för IHB-företag att effektivt implementera AI-verktyg. Slutligen framhäver forskningen nödvändigheten av robusta datalagringsmetoder och kontinuerlig förbättring för att utnyttja AI potential i IHB-projekt.

Nyckelord: artificiell intelligens, maskininlärning, felprediktion, defekter, industrialisering, industrialiserat husbyggande, resursoptimering, kontinuerlig förbättring, byggledning, prefabricering.

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Ahmad Burqan and Khaled Selwaiea

Göteborg, June 2024

List of Acronyms

AI	Artificial intelligence
CI	Continuous Improvement
CPM	Critical Path Method
DL	Deep Learning
EMP	Error Management Practices
GDPR	General Data Protection Regulation
HVAC	Heating, Ventilation, and Air Conditioning
IHB	Industrialized House Building
JIT	Just in Time
KPI	Key Performance Indicator
LPS	Last Planner System
ML	Machine Learning
NLP	Natural Language Processing
OSC	Off-Site Construction
OSI	On-Site Industrialization
PDCA	Plan Do Check Act
PPC	Percent Plan Complete
RCA	Root Cause Analysis

1 Introduction

The construction sector is one of the largest in the world; it is estimated that 10 trillion dollars is the global annual budget of the sector (Mésároš et al., 2024; Wang et al., 2020). Despite its size and magnitude, the construction sector faces a significant challenge of productivity, making it one of the least productive sectors (Wang et al., 2020). An increase of 1% in productivity levels worldwide is estimated to account for 100 billion dollars a year (Wang et al., 2020). Solving the productivity issue is essential for the construction sector to stop it from falling behind the other sectors (Jang et al., 2021). Moreover, the construction sector will require higher productivity levels to reach some of the United Nations' sustainability goals, like increasing resource utilization and meeting the predicted demand for intensified urbanization (United Nations, 2024; Uusitalo, 2020).

One method utilized to help with productivity and sustainability challenges is the industrialized construction method (Stehn & Jimenez, 2023; Uusitalo, 2020). For example, in Sweden, the Million Program utilized the Industrialized House Building (IHB) construction method in 1964 to address the challenge of enormous house demand at the time (Uusitalo & Lavikka, 2021). Industrialized construction is not a new construction method, as it started as early as 1066 in England with the prefabrication of a wooden castle (Mossman & Sarhan, 2021). However, the shift to increased industrialized construction is attributed to multiple factors, like cost reduction, time reduction, and improved quality control (Mossman & Sarhan, 2021). These benefits are achievable due to the nature of industrialized construction, offering a more controlled environment when prefabricating the construction components (Jang et al., 2021).

Utilizing industrialized construction does not remove some of the characteristics of the construction industry. For instance, the construction sector is mainly driven by a project-based system where each project is unique, complex, and varying from other projects based on multiple factors/needs (Uusitalo & Lavikka, 2021). On top of that, the construction sector is characterized as unpredictable and has many variables that lead to uncertainties in the schedule and performance; therefore, it is subjected to factors that lead to delays and cost overruns (Yaseen et al., 2020; Safapour & Kermanshachi, 2019). One of the main causes of delays, cost overruns, and unpredictability is construction errors due to poor quality control in projects; for example, poor workmanship can lead to several errors on the construction site (Mésároš et al., 2024; Jang et al., 2021; Uusitalo, 2020).

To ensure better quality control and avoid extra costs and delays in construction projects, proper planning and proper scheduling are essential (Mossman & Sarhan, 2021). Mossman and Sarhan (2021) discussed the importance of predictability on the construction site to ensure proper planning and scheduling. To help with predictability and limit project variations, AI tools have been utilized to provide multiple benefits, such as rapid and accurate predictions (Yaseen et al., 2020). There are many studies on utilizing AI for planning and schedule management in the manufacturing stage; however, utilizing AI for prediction purposes and decision-making concerning resource allocation and optimization of resources in the on-site construction stage of industrialized construction remains to be further studied (Jang et al., 2021). On top of that, there is a need for an efficient method of on-site decision-making assistance, mainly because it is a time-consuming and expensive task for managers to perform (Wang et al., 2020).

This report will assess the potential for implementing an AI error prediction tool in the on-site stage of IHB construction projects by developing a conceptual framework that can assist IHB companies in implementing AI tools. Furthermore, the report will discuss some benefits, such as achieving better decision-making, optimizing resource utilization in a sustainable approach, and different use cases for such an AI tool in managerial practices. Finally, some recommendations will be provided for what preparations need to be made for companies to embrace AI.

1.1 Aim of the Study

The thesis aims to investigate how AI can be implemented to predict errors in IHB construction companies, specifically focusing on errors in the assembly phase. The study aims to develop a conceptual framework for an AI error-prediction tool that can assist project managers in ensuring better resource planning decision-making in the early stages of the projects.

1.2 Research Questions

- How can Artificial Intelligence be applied to predict construction stage errors in Industrialized House Building projects?

To answer this, the following sub-questions below need to be answered:

- How do IHB companies currently manage construction stage errors, and what are the common causes and impacts of these errors?
- What AI models can be implemented to predict assembly errors in IHB projects?
- What are the potential benefits and challenges of integrating AI technologies into IHB companies?

1.3 Contribution of the Study

This research provides construction companies valuable insight into how AI can be utilized, especially utilizing historical data for prediction purposes. It provides the reader with a road map of how an AI prediction tool could be implemented and states which data will be required. Furthermore, the research discusses potential benefits of implementing such a predictive AI tool, like achieving a more sustainable approach by optimizing resources when planning for the on-site production stage. Moreover, the research is intended to serve as a bridge between civil and software engineers when developing an AI tool. This is done by providing a valuable theoretical foundation on the construction stage (which can help software engineers understand what is needed from the AI tool) and providing some theoretical knowledge on what AI is, and how it can be valuable in the construction sector (which is useful information for the construction sector, to understand what software engineers require when developing such AI tools).

From a research perspective, much of the literature concerning innovation in the OSC has focused on earlier stages, such as factory management, material fabrication, and design stages of IHB projects. This master's thesis, on the other hand, contributed to filling the gap in the literature by delving into AI implementation for planning purposes in the on-site production stage of IHB construction companies. The proposed conceptual framework also provides standardized common error types and error-influencing attributes in the on-site stage of IHB projects that can be utilized for future research. Finally, the authors' contribution to this master's thesis was equivalent throughout the complete process of the master's thesis.

2 Theory

The theory chapter explores key theories related to IHB, planning methodologies, and their associated challenges. It delves into quality control practices, common errors, and an introduction to AI. The insights garnered from this section are pivotal for conducting subsequent analyses and proposing the conceptual framework later in this thesis.

2.1 Industrialized Construction

Industrialized construction marks a transformation in conventional construction methods, incorporating manufacturing design and optimization strategies to solve complex issues in construction projects (Qi et al., 2021). This method emphasizes the significant use of factory-based technologies, focusing on efficient, prefabricated, and modular techniques (Qi et al., 2021). This section will provide an overview of industrialized construction evolution, definition, classification, benefits, and challenges.

2.1.1 Evolution and Definition of Industrialized House Building

To establish the definition of industrialized house building (IHB), it is essential to understand the history behind industrialized construction. Lessing (2006), in his interpretation of some of the older definitions for industrialized construction, cites Jacobsson's (1965) definition: "Industrialisation of construction activities includes a striving to develop and make the production effective, regarding quality and economy by the use of scientific knowledge, repeating work processes in factories, design offices and at building sites, and by the coordination of different activities within and between companies."

Looking back at the history of prefabrication, Mossman and Sarhan (2021) reveal that the concept of prefabrication dates as far back as 1066, with a notable example of a wooden castle prefabrication in England. This historical foundation laid the groundwork for the recent shift towards prefabrication in construction, especially in housing, driven by desires for cost and time efficiency, alongside improved quality control (Mossman & Sarhan, 2021). This shift towards IHB, according to Zabihi et al. (2013), was largely driven by the global housing shortage, which worsened after World War II. They emphasize that this urgent need for housing solutions after the war played a key role in promoting the use of industrialized, cost-effective building techniques.

A notable example of the shift towards IHB in Sweden is the Million Program, initiated in 1964 as a response to the pressing housing demands of the time, as highlighted by Lessing (2006). This initiative was more than just a governmental effort to increase apartment production rates; it was a strategic response to the intense housing demands at the time (Lessing, 2006). Uusitalo and Lavikka (2021) further support this shift by stating that the solution to the high demand for housing in the 1960s was to industrialize the housing industry. According to Stehn and Jimenez (2023), the trend of prefabrication increased by 10% in Sweden between the years 2013 and 2020. The trend of industrialized construction has reached more than 80% of the construction sector in Sweden (Navaratnam et al., 2022). Moreover, according to a recent report by Mordor Intelligence (2024), the market size of prefabricated housing in Sweden is expected to grow by 7% between the years 2024 and 2029.

After exploring the history of IHB and its emergence, Lessing (2006) provided a modern definition of IHB, as a process that integrates various advanced techniques to enhance the efficiency, quality, and reliability of house building. This method includes prefabrication and the use of building systems, along with advanced information technology and logistics, all crucial for successful development. It also leverages past experiences for continuous workflow improvement and employs industrial methods for manufacturing building components.

Chung and Kadir (2006) further expand on the definition by describing IHB as a process where all building components are mass-produced in a factory or an on-site factory according to standardized specifications and then transported to the construction site for assembly. This approach encompasses prefabrication, standardization, and both on-site and off-site construction techniques. IHB is distinguished from conventional methods by its focus on niche markets and the need for more standardized production systems tailored to client needs, as explained by Uusitalo and Lavikka (2021). Additionally, Vásquez-Hernández et al. (2022) highlighted that IHB includes a variety of concepts such as prefabrication, standardization, modularization, manufacturing, and more. A key aspect of IHB is its customer-centric approach, aiming to deliver apartments and residential areas that meet specific customer demands (Uusitalo & Lavikka, 2021).

2.1.2 Classification of IHB

In the realm of IHB, classification plays a key role in understanding the nature and differences of this construction approach. Stehn and Jimenez (2023) emphasize that IHB combines off-site manufacturing, on-site construction, and design within a standardized framework. This approach contrasts conventional house building, which is project-based, often involving a fragmented and less structured network of stakeholders (Stehn & Jimenez, 2023). When it comes to IHB classification, it varies depending on multiple factors, such as market requirements, affecting the degree of off-site assembly and standardization in IHB (Uusitalo et al., 2017; Stehn & Jimenez, 2023).

In this domain, Jonsson and Rudberg (2015) proposed a classification matrix that aligns market requirements and customer needs with the degree of standardization in the production system. This matrix serves as a vital tool for decision-makers, assisting them in optimizing the balance between standardization levels and market needs. When it comes to standardization, Gibb (2001) and Lessing (2006) defined it as the ability to repetitively use processes or components for projects, which is important as it yields cost and time benefits. The proposed matrix illustrates that high standardization results in fewer product types but increased production volume per category, whereas low standardization allows for a greater diversity of products, but in smaller volumes (Jonsson & Rudberg, 2015). This insight is essential for understanding the variety of off-site construction (OSC) approaches, ranging from component production to entirely modular buildings (Jonsson & Rudberg, 2015; Stehn & Jimenez, 2023).

Figure 2-1 illustrates Jonsson and Rudberg's (2015) classification matrix, which is based on two main dimensions: the degree of product standardization, which varies from pure customization to pure standardization, and the degree of off-site assembly. This classification matrix is inspired by Gibb's (2001) classification with slight modification. Table 2-1 below illustrates the findings on the off-site classification system:

Table 2-1 Classification systems based on the degree of off-site assembly.

Classification Category	**Degree of Prefabrication & Preassembly**	**Description**	**Citation**
Component Manufacture & Sub-assembly	Lowest	This category represents the traditional way of construction, like conventional construction methods, featuring the lowest degree of prefabrication and preassembly.	Lessing (2006), Gibb (2001), Jonsson & Rudberg (2015)
Prefabrication & Sub-assembly	Moderate	In this approach, most of the construction process occurs on the actual construction site, while a high level of prefabrication is recognized.	Lessing (2006), Gibb (2001), Jonsson & Rudberg (2015)
Prefabrication & Pre-assembly	High	This category signifies a significant degree of off-site assembly, coupled with a high level of prefabrication. Preassembly is a critical stage where prefabricated components are assembled off-site, marking a departure from traditional on-site building methods and allowing for more efficient construction processes.	Vásquez-Hernández et al. (2022), Lessing (2006), Gibb (2001), Jonsson & Rudberg (2015)
Modular Building	Highest	Described as the highest level of prefabrication and preassembly, this method involves prefabricating volumetric units of room size in a manufacturing facility, fully equipping them with essential fittings, and later assembling them as load-bearing building blocks at the construction site.	Lawson et al. (2012), Vásquez-Hernández et al. (2022), Gibb (2001), Jonsson & Rudberg (2015)

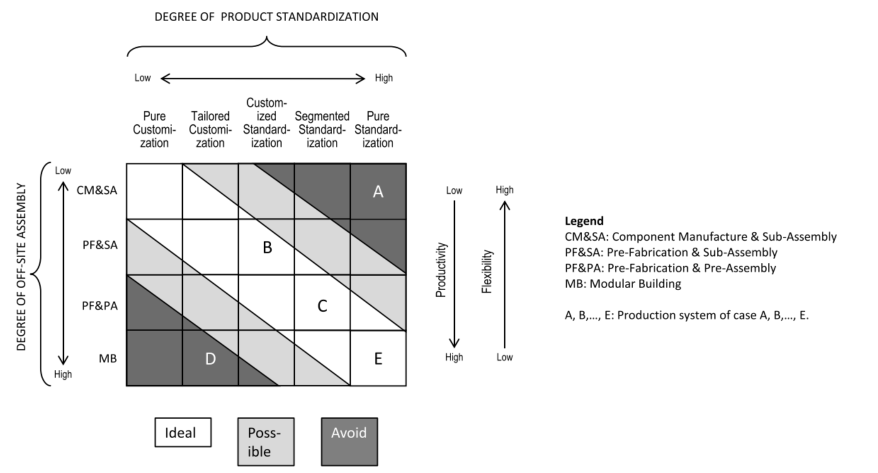

Fig. 3. The revised classification matrix, including classification of production systems for the five cases included in this study

Figure 2-1 Classification Matrix of Off-site Construction (Figure is taken from Jonsson and Rudberg (2015)).

2.1.3 Benefits and Challenges of IHB

Exploring the benefits of IHB reveals a wide array of advantages compared to conventional construction. Jonsson and Rudberg (2015) highlighted significant cost and time reductions achieved through high levels of off-site production. This ensures higher project efficiency in IHB than conventional construction methods (Uusitalo, 2020). In this context, Stehn and Jimenez (2023) reported productivity advantages in their study, where there was an increase of 10% in labor productivity and a 19% improvement in cost productivity growth between 2013 and 2020 for IHB compared to conventional methods in Sweden. Moreover, regarding efficiency, work done in factories ensures greater quality control, reduced noise levels, and fewer disruptions, such as those caused by weather conditions (Blismas et al., 2006; Navaratnam et al., 2022). Furthermore, IHB enables using a task force with lower skill levels, as much of the work is conducted in controlled factory environments, leading to fewer human errors (Uusitalo, 2020).

IHB offers other advantages than cost and time reductions; this is evident as Navaratnam et al. (2022) mentioned that IHB has significant advantages in the realm of safety and sustainability enhancements. Their study highlighted an 80% reduction in on-site incidents compared with conventional construction. When it comes to sustainability, both Navaratnam et al. (2022) and Jonsson and Rudberg (2015) elaborated that IHB practices contribute to a more sustainable approach by reducing the waste generated on-site.

Another benefit of IHB projects is their ability to minimize fragmentation, as highlighted by Stehn and Jimenez (2023), where fragmentation is one of the hindrances that the construction industry faces and limits the area for innovation (Hughes & Stehn, 2019; Andersson & Lessing, 2017). Stehn and Jimenez (2023) explained that IHB systems help to reduce vertical fragmentation (e.g., by utilizing long-term contracts with suppliers) and horizontal fragmentation (e.g., by integrating most construction stages in the design phase).

On the other hand, there are some challenges to implementing IHB. The shifting dynamics of the construction market, as discussed by Uusitalo and Lavikka (2021) and Koskela (2000), demand a high degree of adaptability from IHB companies, particularly in managing short-term site variations that require a broad resource base. On top of that, standardization, which is central to IHB projects, poses challenges in meeting diverse customer demands. In the case study by Uusitalo and Lavikka (2021), the studied IHB company strived to reach out to customers in advance to explain the benefits of their production system. On top of that, the IHB company strived to spread knowledge about their systems through other platforms, like collaborating with university students to explore and spread knowledge about their IHB production system.

Navaratnam et al. (2022) also shed light on multiple challenges in different stages of IHB projects, as they highlighted that IHB companies have to deal with the high cost of establishing the factory for the prefabrication of components and modules. Another mentioned obstacle in their article relates to the limitations in design flexibility, due to IHB's standardized nature of components, which can constrain architectural creativity. Moreover, IHB components have limited tolerance in the factory production and assembly phase, where errors significantly impact the project's cost and time (Navaratnam et al., 2022).

From a logistical perspective, transportation challenges emerge, as IHB products are usually large, and transport to urban areas could be limited or challenging (Navaratnam et al., 2022). Additionally, synchronization between the factory and the production site is critical since variations that appear can have detrimental effects. For example, the task force and resources might have high idle time if elements are delayed in arriving on site (Mossman & Sarhan, 2021; Navaratnam et al., 2022).

2.2 Assembly and Construction Stage

The planning, preparation, and coordination of the construction/assembly stage are crucial for IHB projects' success (Lessing, 2006). Errors in these stages of the IHB projects can have detrimental effects, leading to catastrophic results in some cases (Lessing, 2006). This is why proper coordination and synchronization in IHB projects concerning the assembly stage are vital for the success of projects (Mossman & Sarhan, 2021). It is important to acknowledge that industrialized construction is not limited to the production of components in factories; in fact, the IHB systems stretch out to the production stage, including even the processes of production that happen on-site (including less prefabricated processes) (Andersson & Lessing, 2017). This section will discuss some of the planning methods, challenges, and errors that can occur in the construction stage of IHB projects.

2.2.1 Planning Methods

The assembly planning phase in IHB projects is a key area where strategic planning methods are critical for the efficient and successful execution of projects. This is because, despite IHB's advantage of shorter project durations, various schedule risks still exist, necessitating the use of optimized scheduling and planning models (Qi et al., 2021). This thesis subsection will focus on some of the planning methods essential in managing processes in IHB projects. Moreover, the subsection discusses the need for effective coordination and integration of various activities, further explores how these methods contribute to streamlining workflows, and explores some areas of lean strategies and techniques to minimize waste and enhance overall project efficiency.

Figure 2-2 Core tenets of Lean (Figure is taken from Lean Construction Institute (2024)

In the context of Lean Construction, respect for individuals forms the foundation upon which its core tenets are built, as highlighted by the Lean Construction Institute (2024) and shown in Figure 2-2. This core tenet underscores the importance of increasing customer value in construction projects, as emphasized by Lessing (2006). Lean methodologies aim to eliminate waste, reduce variations, and enhance predictability in construction processes (Lean Construction Institute, 2024). Key techniques employed in Lean practices include planning strategies like the Last Planner System (LPS), the Critical Path Method (CPM), and the Just-in-Time (JIT) delivery (Lean Construction Institute, 2024). These planning methods, as discussed by Mossman and Sarhan (2021), are crucial in streamlining construction workflows, thereby optimizing project outcomes in the realm of IHB.

Last Planner System (LPS)

According to Koskela (2000), The Last Planner method, developed by Ballard and Howell in the 1990s, is a significant advancement in construction production control. It is based on five core principles that aim to enhance efficiency and minimize variability in construction projects (Ballard, 2020). These principles include ensuring all necessary components are available before performing a task, monitoring task completion through the Percent Plan Complete (PPC) metric, addressing and rectifying reasons for incomplete tasks, maintaining a task buffer for crews, and utilizing lookahead planning to prepare for upcoming assignments (Ballard, 2000). This method effectively combines control and improvement to reduce variability and associated waste, ensuring predictability, and fostering more reliable deliveries and schedule adherence (Lean Construction Institute, 2024). LPS is a practical approach to finding optimal solutions for common challenges in construction project management (Ballard, 2020; Mossman & Sarhan, 2021; Lean Construction Institute, 2024).

Critical Path Method (CPM)

The Critical Path Method (CPM), developed in the 1950s, is a fundamental planning approach in construction planning as it structures project schedules through a network of linked tasks, emphasizing logic and sequence (Scala et al., 2022). Some concepts that CPM utilizes are work breakdown structures and critical path identification, which is often visualized via Gantt charts (Scala et al., 2022). Despite its limitations and complexities, including challenges in adapting to project changes and dependency on experienced practitioners, CPM remains widely used and is often required in contracts (Scala et al., 2022). Its enduring popularity in construction is attributed to its ability to guide project control, decision-making, and subcontractor coordination (Scala et al., 2022). Furthermore, Koskela (2014) explains that this is due to the transition in the usage of CPM, shifting from planning tasks as production control to emphasis on contract control.

Just-In-Time Method (JIT)

Lessing (2006) explained JIT and its goal by highlighting that: "The goal is that every process should be provided with the right part, in the right quantity at exactly the right time. The vision is to produce one piece at a time, exactly when it is needed. Different types of products and parts require different levels of JIT." According to Lean Construction Institute (2024), JIT material management is a method that is used to better organize and coordinate material transportation in construction projects solving unnecessary transportation issues. The effects of unnecessary transportation led to waste generation in construction projects and multiple challenges like overstocking on the construction site, leading to less efficient material management or even causing extra errors and defects that can happen on-site (Lean Construction Institute, 2024).

2.2.2 Barriers and Challenges of Planning

Many of the construction projects are designed and produced in a temporary production system manner, causing variability and increasing unpredictability (Wu et al., 2021). These impact projects include increasing the buffering time between flows or lowering resource utilization (Ballard, 2020). Moreover, construction projects differ from one another, causing planning inefficiency as the planning process is done on a project basis and not on a company basis (Wu et al., 2021). Unpredictability and variability challenges intensify when involving many stakeholders in the same project, as this creates coordination and communication issues regarding knowledge transfer between the different stakeholders in different project stages (Grenzfurtner & Gronalt, 2020).

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Another form of knowledge transfer problem occurs in projects when many problems are solved on-site without properly defining the problems and reporting them, thus limiting and reducing the significance of the continuous improvement (CI) of the planning process, which requires learning from prior problems or variations (Meiling et al., 2012). The study by Meiling et al. (2012) suggests that a top-down and bottom-up approach is required to solve this issue and facilitate the integration of CI and lean concepts, establishing a lean mentality in IHB companies. Another important factor for the success of CI in planning IHB projects is the integration of subcontractors into the CI processes, which requires long-term relationships to ensure the willingness of subcontractors to engage (Grenzfurtner & Gronalt, 2020).

When it comes to planning methods, many methods, such as CPM and LPS, have several shortcomings and limitations, as they rely on project managers' and other stakeholders’ experience, judgment, variations in output rate, and more (Scala et al., 2022). For instance, the LPS has challenges due to having a huge data load that might require proper information management system handling by professionals (Scala et al., 2022). CPM, on the other hand, as highlighted by Koskela et al. (2014) and Mossman and Sarhan (2021), has a limitation when it comes to producing predictable outcomes, as CPM plans are not regularly updated.

Other than specific planning method challenges, defects and error-related issues affect the scheduling and planning of construction projects (Johnsson & Meiling, 2009). Yaseen et al. (2020) highlighted that defects and errors cause delays in construction projects, which impacts the projects’ timeline, as errors require rework or some adjustments.

2.2.3 Errors in the Assembly and Construction Stage

The assembly and construction stage in IHB projects is a critical stage where prefabricated components, which are transported to the construction site, are assembled according to project designs and specifications. As mentioned in the section above, one of the main factors affecting planning and scheduling is defects and errors in the construction/assembly stage (Yaseen et al., 2020). Qi et al. (2021) highlighted significant risks during this stage, including challenges like the inefficient verification of components, breakdowns of critical equipment like cranes, and delays in maintenance or installation of elements (Qi et al., 2021). These risks underscore the need for robust and efficient systems to manage component tracking, on-site storage, lifting, assembling, and shed light on quality inspection, ensuring the smooth and timely completion of the assembly process (Qi et al., 2021).

Furthermore, the importance of having more efficient systems is evident as much of the material handling processes on-site are done manually and on paper, which is both time-consuming and increases the risk of errors happening at the construction stage, as highlighted by Zhou et al. (2021). They discussed that working efficiency can be affected negatively by unexpected events, like changes and delays in the project’s schedule. Moreover, the problem intensifies when the stakeholders are not aware instantly of the errors or the changes, lowering their decision-making impact when information is not delivered to them at the right time (Zhou et al., 2021).

2.2.3.1 Consequences of Errors on Projects

Errors in construction projects have a variety of consequences that can affect the project and the company negatively, influencing both organizational performance and customer satisfaction (Forcada et al., 2013). In this context, many studies discussed multiple consequences of defects on projects in the construction sector, like delays, cost overruns, and effects on schedules (Forcada et al., 2013; Forcada et al., 2015; Jonsson & Gunnelin, 2019; Safapour et al., 2019; Saha et al., 2023).

From a financial perspective, Paton-Cole and Aibinu (2021) highlighted that rework arising from defects could account for 2% to 5% of the total contract price, directly reducing profit margins. Forcada et al. (2015) discussed that the impact of defects goes beyond the financial and temporal dimensions of a single project, affecting the end-users and, consequently, the reputation of the construction firm. Poor outcomes from construction projects can lead to lower customer satisfaction, which in turn may damage a company's reputation and its future business prospects (Pan & Thomas, 2015; Paton-Cole & Aibinu, 2021). Additionally, Jonsson and Gunnelin (2019) discussed the broader implications of defects on building occupants, suggesting that unresolved construction issues can cause significant psychological stress for residents, negatively affecting customer satisfaction and company reputation.

Since the frequency and number of errors are important indicators of housing quality, as Pan and Thomas (2015) noted, it is crucial to mitigate project errors. This emphasis highlights the importance of quality control and CI in construction practices to mitigate the occurrence of errors, as defects and rework critically affect the decision-making process and project management outcomes (Nabi & El-Adaway, 2020). The subsequent section on CI will delve into strategies and methodologies that construction firms adopt to enhance their quality assurance processes and decision-making frameworks, aiming to reduce the frequency of defects in projects and improve overall project outcomes.

2.2.4 Quality Control

As specified in the previous section, quality control and CI are important to mitigate defects in construction projects. Liu et al. (2022) stated that errors like cracks in components reduce the development of OSC projects. To solve the problem of errors, they stated that quality control in OSC projects is critical to ensure continuous development. This section will discuss some areas and methods that significantly affect quality control.

2.2.4.1 Continuous Improvement (CI)

Meiling et al. (2013) stated that "The purpose of CI is the identification, reduction, and elimination of sub-optimal processes, i.e., efficiency, with a focus on continuous incremental steps rather than major innovation leaps." Implementing CI practices in construction projects helps mitigate errors that are usually handled reactively, resulting in incremental improvements. Juran's quality trilogy, shown in Figure 2-3, which was introduced in 1986 for enhanced quality improvements, provides valuable insight into the realm of CI as described by Johnsson and Meiling (2009). They further discussed the ability of this trilogy to mitigate chronic waste in production through learning from production's shortcomings and incrementally improving to further include improvements in future planning processes.

Furthermore, Stehn and Jimenez (2023) argue that standardization, CI, and systematic learning are efficient methods to reduce and limit fragmentation and increase productivity in construction. Lean principles, in general, as discussed in previous sections, have a common goal of reducing waste and unwanted activities and aiming for CI in the project (Koskela, 2000; Meiling et al., 2012; Lean Construction Institute, 2024).

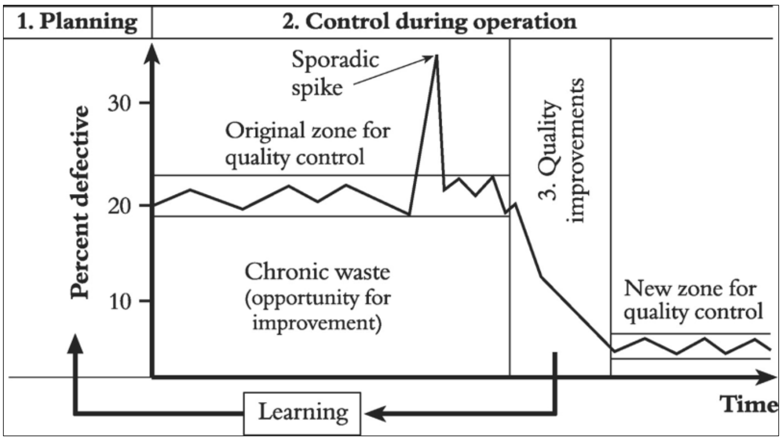

Figure 2-3 Juran Quality trilogy (Figure is taken from Johnsson and Meiling, (2009))

2.2.4.2 Root Cause Analysis (RCA)

To reduce or diminish project errors, many methods, tools, and techniques can be utilized. One of the techniques is called the Root Cause Analysis (RCA), which was developed by Kaoru Ishikawa (Lean Construction Institute, 2024). RCA aims to find the reason/root cause behind errors, by conducting what is called "The 5 whys" of lean as stated by the Lean Construction Institute (2024). According to the institute, the 5 whys is an analysis strategy of asking at least 5 times for the reason of a certain error/problem happening to land at the root of the problem.

2.2.4.3 Plan-Do-Check-Act (PDCA)

PDCA, which is illustrated in Figure 2-4, is a cycle that was developed for the automotive industry in the 1950s (Ghansah & Edwards, 2024). As described by Ghansah and Edwards (2024), the cycle begins with planning, where the challenge/problem is studied, and a solution for the problem at hand is developed. According to them, the second step is to do the testing on a trial basis for the proposed solution while taking measures. The third step is checking where the assessment of the experiment's effects/results is studied (Ghansah & Edwards, 2024). Finally, if the experiment is a success, then the Act phase is where the process becomes standardized and established into the processes of the project (Ghansah & Edwards, 2024).

Although the process seems valuable, it has its own shortcomings. PDCA is resource-intensive, which is one reason why it has not been implemented enough in the construction industry (Meiling et al., 2013). However, the usage of PDCA in the construction industry was mainly conducted to reach certain goals in projects, like cases that needed urgent solutions (Meiling et al., 2013). However, the study by Meiling et al. (2013) shows that PDCA can be used as a method of deviation reduction in less industrialized construction companies. They argued that it helps the users by finding the root cause of the deviation, especially if combined with tools like the Ishikawa diagram to isolate the cause of the problem.

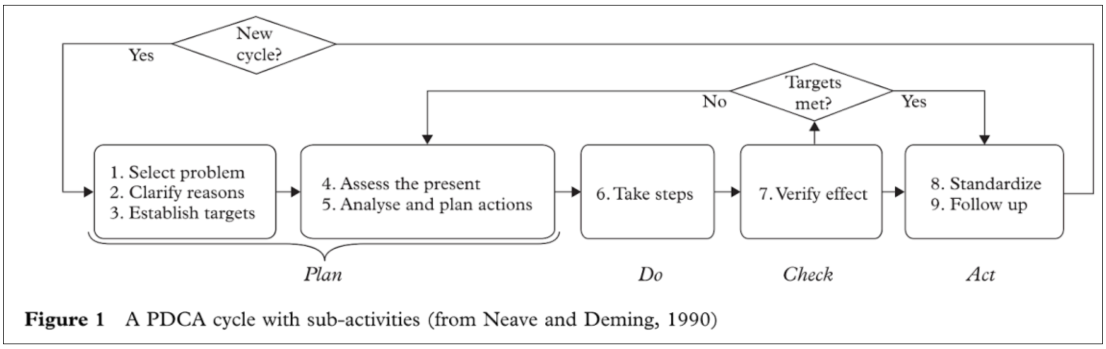

Figure 2-4 PDCA cycle with the sub-activities (Figure is taken from Meiling et al. (2013))

2.2.4.4 Mistake Proofing

Poka Yoke, or rather Mistake Proofing, was invented by Shigeo Shingo in Japan, who is considered one of the factors for the success of Toyota (Zavichi et al., 2010). The authors Zavichi et al. (2010) described mistake-proofing as a method that focuses on reducing the need for inspection by implementing a mistake-proofing device/method that eliminates the chance of the error happening in the future. They proposed methods that can be used as mistake proofing, like standardization, modularization, automation, and visual management, to reduce errors in construction sites.

An example of mistake-proofing in construction is a vision-based detection system, as shown in the study by Bae and Han (2021). They explored a vision-based solution to show project errors using projectors and sensors to compare the as-planned product with the built product.

2.3 Artificial Intelligence (AI)

Although Wang (2019) states that there is no clear, widely accepted definition for Artificial Intelligence (AI), AI can be broadly defined as a technology that enables computers to mimic human intelligence and analytical skills (Shinde & Shah, 2018; IBM, 2024). AI can be combined with a range of technologies that allow machines to sense, comprehend, act, and learn, enabling them to perform tasks that typically require human intelligence; this includes complex decision-making, visual perception, language understanding, and pattern recognition (IBM, 2024). According to IBM (2024), AI includes Machine Learning (ML) and Deep Learning (DL), where DL is a part of ML as shown in Figure 2-5.

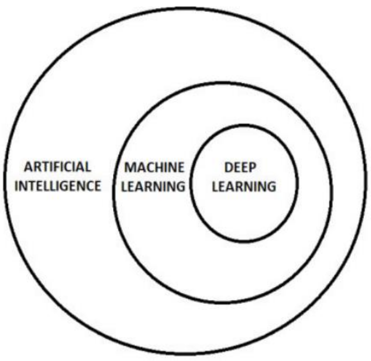

Figure 2-5 AI domains consisting of ML and DL, (Figure is taken from Chauhan and Singh (2018))

2.3.1 Machine Learning (ML)

ML, including its subfield of DL, enables automatic data classification and identification, utilizing algorithms for analysis and decision-making (IBM, 2024). Traditional ML methods require expert-driven feature selection, whereas DL automates feature extraction from raw data, enhancing its processing capabilities (Chauhan & Singh, 2018). Both ML and DL use supervised learning for specific target-driven tasks and unsupervised learning for tasks like clustering without predefined targets, making DL more efficient due to its ability to learn complex input-output relationships without manual intervention (Chauhan & Singh, 2018).

In the construction industry, ML algorithms are used to predict project outcomes in terms of cost and time, optimize resource allocation, and enhance safety measures (Abioye et al., 2021). For instance, ML can predict potential failures or maintenance needs by analyzing data from sensors embedded in structures (Bouabdallaoui et al., 2021). Table 2-2 below, inspired by IBM (2024), shows the most common supervised and unsupervised learning algorithms.

Table 2-2 Some of the algorithms utilized in AI (inspired by IBM (2024))

Algorithm	Supervised/ Unsupervised	Description	Applications
Neural Networks	Both Supervised & Unsupervised	These networks replicate neural structures in the human brain to handle pattern recognition, supporting complex task performance.	Language translation, image, and speech recognition, and creative image generation.
Linear Regression	Supervised	Predicts outcomes by establishing a linear equation to variable relationships, commonly used for forecasting and trend analysis.	Pricing predictions, economic forecasting.
Logistic Regression	Supervised	Provides probability estimations to classify data into binary categories, ideal for binary decision-making processes.	Email spam detection, pass/fail quality testing.
Clustering	Unsupervised	Group data are based on intrinsic similarities, enhancing the identification of patterns and categories within datasets.	Consumer market segmentation, data pattern analysis.
Decision Trees	Supervised	Structures a series of decision points into a tree-like model, simplifying the process of data classification and regression.	Medical diagnosis, financial risk analysis.
Random Forests	Supervised	Integrates multiple decision trees to improve reliability and accuracy in predictive outcomes, reducing the risk of error in individual trees.	Wildlife habitat prediction, stock market trends analysis.

2.3.2 Natural Language Processing (NLP)

Natural Language Processing (NLP) stands out for its ability to analyze and interpret human language, making it applicable in many areas of the construction industry, such as health and safety, contracts and conflicts management, project planning, and knowledge and risk management (Khurana et al., 2022). NLP is a part of ML concerned with enabling the computer to mimic human linguistic capabilities; for example, NLP can help with summarization, speech recognition, chunking, text categorization, information extraction, and role labeling (Abioye et al., 2021; Khurana et al., 2022).

3 Literature Review

The literature review chapter delves into recent literature concerning the various dimensions of errors within IHB projects, focusing on their classification, commonality, consequences, causation, and avoidance strategies. The chapter further explores the integration of planning and predictive technologies, particularly AI, in mitigating on-site errors. The insights from this review are crucial for identifying the gap in the existing research and assisting in developing the conceptual framework for error prediction IHB projects.

3.1 Classification of Errors

Several definitions/words represent errors that happen in the construction industry. Macarulla et al. (2013) defined errors by saying: “In the building industry, words like error, fault, failure, defect, quality deviation, nonconformance, quality failure, and snag are used interchangeably to describe imperfections in constructed buildings”. In this context, there have been several research/studies within the realm of errors in the construction stage. This section will discuss some of the literature related to the classifications of errors in terms of types, location, related phase, most common, consequences, and causation.

Johnsson and Meiling (2009) conducted an in-depth study on defects in OSC, specifically focusing on timber module prefabrication. This study analyzed the design and manufacturing processes at two Swedish timber module prefabrication firms. Quality audits from three phases of the building process (factory, final, and warranty inspection records) were compiled and categorized utilizing 17 housing projects. The study found defects in industrialized housing were generally lower than in conventional housing, suggesting better product quality due to the controlled off-site manufacturing environment. Defects in IHB projects were categorized based on the following questions: “Where did the defect occur?”, “What was defective?”, “What type of defect was it,” “What measures were taken to correct the defect?” “Why did the defect occur (root cause),” “When did the defect occur?”. The results show that most errors are human error types both in the factory and on-site.

In an article by Forcada et al. (2015), the comparison between construction and post-handover defects is brought up as the authors believed there seems to be a gap in assessing quality. This is because the quality perceived by the customer might vary from that perceived by the contractor. The comparison findings provided a surprising outcome, showing that some of the defects detected during the construction stage persist even after the post-handover stage. Their study classified the defects by type of defect, type of building element, and defects by subcontractors. One important outcome of this study indicates that significant implications arise from having defects at the post-handover stage, as rectifying the errors in this stage requires more resources in terms of manpower and time.

Many studies classified construction defects based on other factors such as defect numbers, location, area, and defect severity (Pan & Thomas, 2015; Jonsson & Gunnelin, 2019). For instance, Park and Seo (2021) defined severity based on the frequency of defect repetition in projects and the cost of repairing the defect. On the other hand, in the study conducted by Pan and Thomas (2015) about the classification of errors in terms of severity and area, they defined severity based on the “number of days in which defects need attention.” Their findings indicate that only around 8% of the defects required rectification as fast as possible (within 24 hrs). However, 34% of the defects needed attention within two weeks, and 31% of the errors required rectification within the warranty period (one-year post-handover).

To minimize defects in the construction industry, a proper standardized classification system is required. Park and Seo (2021) proposed such a system for timber construction in Korea after considering 100 appraisal reports and decisions for housing complexes, where they listed the critical defects in a standardized format. In their standardized classification system, 63 standardized error items were proposed to include all of the errors from the collected data. These error items were categorized based on the time of the defect (during construction or post-handover), work type, location/building component (like the ceiling), object (further specifying the area within the building component, like the frame of the ceiling), and Phenomena (where the type of the error is explained, like missing work or unmatched size). The table, including the 63 error indexes, is provided in the appendix of this report.

In order to create a proper standardized classification, it is important to identify the characteristics and attributes of the project. In this context, Mésároš et al. (2024) conducted a systematic literature review of 56 papers that discussed factors influencing defects, where they listed some of the characteristics of buildings that contribute to or cause defects. These include the structure's age, type of building, its dimensions, orientation, and complexity. Similarly, Pan and Thomas (2015) stated that attributes like dwelling type, floor area, and the number of rooms/bedrooms are some of those influencing factors that can change the characteristics of the defect in terms of magnitude and appearance.

On the other hand, Safapour et al. (2019) examined the managerial aspect. They classified the indicators of manageable rework causes into three categories and further classified them into 13 attributes within the following categories: organization, project, and people. The article indicated that the project management team carries the heaviest weight in importance, as they are responsible for planning the project, leading an effective team, and monitoring the project's success.

3.1.1 Most Common Errors

When it comes to common types of errors, Johnsson and Meiling (2009) classified them into five categories: missing, unfinished, broken, erroneous, and unrelated. Their results show that most errors, up to 50%, are erroneous in type, while broken, missing, and unfinished are between 10 and 20% in final audits. However, most error types were erroneous and broken in the warranty audits.

Forcada et al. (2015) indicated that the most common error type during construction is usually the stability of roofs and facades. It is worth noting that their study attributed these errors to poor craftsmanship and inappropriate installation methods. On the other hand, errors that are reported post-handover mainly had functional issues like missing some elements, having a mess in the property, or other issues like cracks, and scratches on surfaces. Their study found that the most common error types in the handover defects were surface appearance (64.5%), followed by tolerance errors (9.3%, which includes dimensional errors), and affected functionality (6.8%). When it comes to defects by building element, the report shows that internal walls (59.9%), windows (17.2%), and mechanical and electrical systems (8.5%) had the highest defect percentages.

Similarly, Macarulla et al. (2013) findings indicate that inappropriate installation had the highest percentage of errors during the construction stage, followed by missing items, and surface appearance. On the other hand, missing items, dirty, and affected functionality were the most common errors in the post-handover stage. Jonsson and Gunnelin (2019) also indicated that the most common post-handover complaint from the customer is usually functional or aesthetical errors.

When it comes to the location of defects or the area where defects are found, many authors divided the errors by different locations, for example, openings, outdoors, dwellings, and such (Johnsson & Meiling, 2009). However, when it comes to specific areas, the kitchen and bathrooms were the most common locations for errors (Pan & Thomas, 2015). This insight is similar to Boverket's (2018) report on the construction industry in Sweden, where they reported that the most common errors were related to water leakage in roofs, exterior facades, and leakage from pipes.

3.1.2 Causation of Errors

Lack of communication, coordination, and detailed work standards are some of the causes of errors, that Safapour et al. (2019), Johnsson and Meiling (2009), and Boverket (2018) highlighted. These causes usually include inaccuracy in prefabricated material tracking and diversifying team solutions/practices, intensifying communication and coordination problems (Jonsson & Gunnelin, 2019). Moreover, the study by Johnsson and Meiling (2009) shows that bad craftsmanship and structural errors are the root causes of errors.

Safapour et al. (2019) and Jingmond and Ågren (2015) discussed poor project management as the leading cause of errors. Jingmond and Ågren (2015), in their study of defects' root causation, also highlighted the lack of proper mistake feedback and lack of knowledge transfer-related issues as some of the main root causes of defects. Boverket (2018) also discussed time constraints as one of the highest contributors to errors.

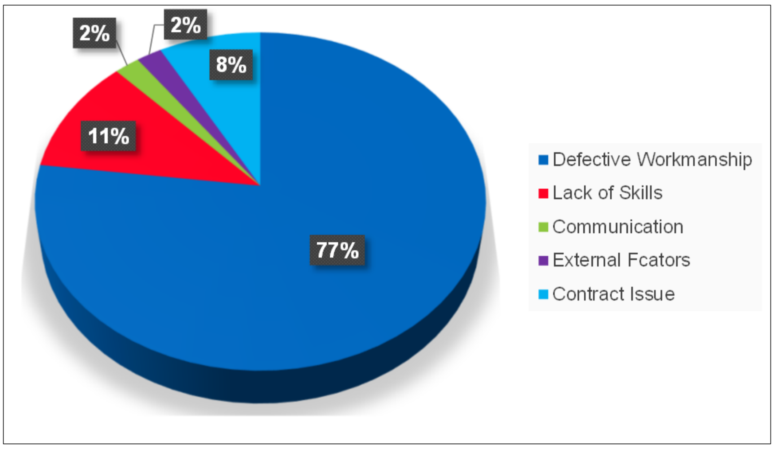

Figure 3-1 Causation of Errors in Construction Disputes Related to Defective Construction Work, (Figure taken from Wu et al. (2019).

Paton-Cole and Aibinu (2021) explored the causes, root causes, and triggers of defects, by investigating post-handover defects in 10 landmark cases. In the study, poor supervision, poor documentation, and poor communication were the main root causes of defects in the low-rise residential building. It is worth noting that the most repeated root cause in almost all of the cases was poor supervision. Moreover, the proximate causes of the defects were mainly because of poor workmanship aligning with the aforementioned findings (Wu et al., 2019; Paton-Cole & Aibinu, 2021). The findings by Wu et al. (2019) of the 100 construction work-related disputes show that the highest contributing factor of defects in disputes was defective workmanship with 77%, while the other factors' contribution, shown in Figure 3-1 contributes to a total of 33%.

3.2 Error Mitigation and Prediction

In the domain of IHB, the integration of planning and predictive technologies plays a crucial role in error mitigation and enhancing project outcomes. This section of the literature review explores various strategies and innovations that affect error mitigation and efficiency improvements from the early project stages, such as the initial planning and design phase.

Several studies underline the importance of adopting early solutions to limit and mitigate errors in projects (Jonsson & Gunnelin, 2019; The Lean Construction Institute, 2024; Safapour et al., 2019; Lessing, 2006). For instance, Jonsson and Gunnelin (2019) underlined the importance of addressing potential defects early in the planning stage, where decisions about material selection and workmanship have significant impacts on project quality. Similarly, Safapour et al. (2019) argued for the benefits of implementing best practices early in the project. Their study demonstrated that many rework causes can be effectively mitigated through early intervention. However, they stated that some external factors, such as weather and financial constraints, are beyond the control of project teams.

Additionally, The Lean Construction Institute (2024) emphasized the necessity of creating a predictable and reliable workflow in construction projects. They argued that, by increasing predictability, the construction process becomes more efficient and less susceptible to errors, thus impacting variations and non-conformance that are found in construction projects. A different approach to minimize errors in the assembly phase of IHB projects is the segmentation of projects into smaller, modular components, as highlighted by Lessing (2006). He discussed that this method could decrease errors by as much as 50%, illustrating the effectiveness of managing smaller, more controlled segments of a construction project.

From a technological perspective, the advancements in predictive modeling provide potential benefits for error mitigation, assisting project managers (Qi et al., 2021). For instance, Li et al. (2018) developed a predictive model that uses various delay factors, including defects and errors, to accurately forecast assembly schedules in prefabricated construction. This tool has proven effective, with test results showing minimal error factors below 3%. Similarly, Mardiani (2018) proposed a risk assessment tool that helps in identifying potential delays, allowing for better scheduling and time management throughout the construction process. Additionally, the incorporation of AI and ML into IHB projects is transforming data analysis capabilities, as noted by Qi et al. 2021. They discussed the substantial benefits of employing these emerging technologies, such as enhanced decision-making and improved management of complex construction activities.

Overall, these studies collectively emphasize that the early integration of planning and the adoption of predictive technologies are essential for minimizing errors and optimizing project outcomes in the field of industrialized construction.

3.3 AI for Prediction in the Construction Stage

Several studies demonstrated the significant benefits of AI and ML in enhancing decision-making processes, particularly in the realm of errors, their causes, and consequences (such as delays and rework) (Alsakka et al., 2023; Fan, 2021; Fan, 2020; Yu et al., 2019; Lee & Hyun, 2019). These studies show the importance of these technologies in improving the accuracy of project outcome prediction, such as time and cost, which are crucial for effective project management. Ghansah and Edwards (2024) discussed that AI and ML can be beneficial tools for decision-making, especially when there is a lot of data that needs to be analyzed, as ML can help with fast analysis to gain faster interpretation of the huge amounts of data, assisting in the process of quality assurance of projects.

In the realm of error prediction using AI, Fan (2020) utilized ML models to predict the probability of errors happening in construction projects. The author also categorized the risk level of errors, classifying 11 of them in the high-risk error category, where many of these errors are related to different stakeholders within the project. In the context of stakeholders, Yu et al. (2019) investigated their effect on defects in OSC projects. This was done through an ML model conducted on a construction project in China, where they found out that the contractor has the highest impact on quality defects.

In order to predict errors, attributes that cause rework have to be analyzed and characterized. Forcada et al. (2017) studied the attributes that contribute to rework cost in projects, where the characteristics of the project were input into the regression model. Their study found that the contract's original cost and the project's location in relation to the company's headquarters were the most contributors in terms of cost. Moreover, relating to the effects of attributes, Fan (2021) conducted both supervised and unsupervised ML models in their study on conventional construction projects, where they focused on the relationship between defects and attributes. One of the study outcomes listed the most significant errors, such as errors concerning concrete quality, inspection of tools, materials, construction work, construction log, and quality control checklist.

To minimize errors and enhance the construction stage of IHB projects, Lee and Hyun (2019) conducted a study to consider utilizing algorithms in scheduling. Their approach was to consider the whole cycle of modular construction projects, beginning with the factory and ending with the on-site assembly. This is done to better develop a planning schedule including sequencing of the whole process.

The utilization of AI for estimation and prediction is not only used for the analysis and preprocessing of the data. In a literature review study of computer vision applications in OSC by Alsakka et al. (2023), both the advantages and challenges of using real-time vision-based defect prevention methods were discussed. These methods can help with real-time error prediction for the on-site assembly stage of IHB projects, eliminating some of the time losses associated with manual inspection and control of on-site quality.

Other than predicting errors, some articles utilized AI prediction for some of the consequences of errors, like delays, rework, and cost (ex, Ali & Abd, 2021; Gondia et al., 2020; Yaseen et al., 2020). For instance, Ali and Abd (2021) conducted an experiment to predict delay and cost in construction projects, where ML techniques were utilized to predict outcomes using risk factors and delay factors. Their findings indicate that ML, in fact, had acceptable accuracy in predicting cost and delays. It is worth noting that their prediction model was a better fit for predicting cost rather than delays.

In the same context, Gondia et al. (2020) and Yaseen et al. (2020) conducted similar studies where various ML models were utilized to predict project delays, such as Decision Tree, Naïve Bayesian ML classification algorithms, and Random Forest classifiers. The study by Gondia et al. (2020), proved that the Naïve Bayesian model is more suitable for the prediction of delays, achieving better results when compared with the Decision Tree ML model. Yasseen et al. (2020), on the other hand, achieved the highest accuracy of 91.67% when using the "integrative Random Forest classifier with Genetic Algorithm optimization (RF-GA)".

A challenge that faces the analysis of data in construction, is the fact that much of the data is saved in an unstructured format (Lauble et al., 2023). This causes complications and further manual preprocessing like interpretation and classification of the data; such activities are time-consuming, as highlighted by Lauble et al. (2023). In their article, NLP was conducted to achieve an automatic mapping system of performance. Their prototype gained promising results when compared with the LPS results, indicating high predictability rates. In a similar approach to minimize time and effort, Martinez and Cisterna (2023) considered using low-code AI algorithms to enhance the digitalization process and achieve CI in the construction industry. Their study shows promising time savings of up to 78%, this was done by automating data processing of on-site paper-based delivery notes.

Koç et al. (2024) discussed that there are many studies conducted on ML for prediction in construction. However, they indicated that most of the prior studies on ML and prediction in construction focused on some of the factors and did not include all potential factors that could affect the prediction model. In their study, 53 attributes were included utilizing random forest as an ML model, where they studied the cost impact of nonconformances on project outcomes. Furthermore, there are limited studies on the prediction regarding quality and performance in projects, as the articles' efforts are mainly placed on cost, delay, and rework (Koç et al., 2024). This opens the door for more studies to be conducted on the cost of quality and performance-related issues, such as error prediction in IHB projects.

3.3.1 Challenges of AI Implementation

Andersson and Lessing (2017) cited Winch (2010) when describing construction management, saying, "Construction management is a problem of information—or rather lack of information," which clearly shows the problem that the construction sector suffers from. They added that the problem with data in the construction industry is a challenge of having common standards and classifications, further increasing the rate of data re-entry.

Furthermore, the Lack of digitalization in the construction industry leads to complexity in the management of projects and inefficiencies, such as delays, insufficient quality, and poor decision-making (Abioye et al., 2021; Fachrizal et al., 2020). According to Stehn and Jimenez (2023), IHB projects struggle with CI, specifically with on-site data collection and analysis. Their study shows that the IHB construction companies suffer from insufficient data reporting, especially time-related data. For example, only 86 of the 103 projects that have been studied had recorded data when it comes to lead time (Stehn & Jimenez, 2023). Macarulla et al. (2013) provided standardized classification processes to face the challenges faced by the construction industry. They stated that there is a problem with data structure, which reduces the ability to utilize and analyze historical data.

3.4 Research Gap

According to the theory and literature review chapters, within IHB projects, which are characterized by their standardized and systematic nature compared to traditional construction methods, a notable research gap emerges in the integration and application of CI practices. Andersson and Lessing (2017) highlight that the standardized nature of IHB projects facilitates easier monitoring and application of CI practices, presenting a unique advantage over conventional construction methods.

Despite the recognized benefits of data from inspection records for feedback and CI within the construction sector, these records are predominantly maintained in paper form or as PDF files, which limits their utility for data-driven decision-making (Lundkvist et al., 2010). The construction industry, while aware of the potential benefits of empirical data, tends to rely heavily on experiential expert knowledge (Lundkvist et al., 2010). The integration of ML with expert insights is proposed as a more robust approach for enhancing decision-making in construction. However, Barkokébas et al. (2023) indicate that research on automation in OSC remains scant, suggesting a significant gap in leveraging advanced technologies for improving construction processes.

Moreover, Johnsson and Meiling (2009) and Macarulla et al. (2013) discuss the potential of utilizing historical analysis alongside error categorization as effective tools for quality improvement. Similarly, Wu et al. (2021) argued that ML techniques to predict resource utilization through previous historical data could fill the gap of incorrect resource utilization estimated by humans when planning for new projects.

When it comes to NLP, Abioye et al. (2021) argued that although there is huge interest in ML applications in construction projects, minimal studies were conducted in the construction industry about the usage of NLP, making it the least researched area of AI in construction.

Building on these identified gaps, this research aims to explore the utilization of documented historical errors and defects from projects’ historical data to predict potential issues in future projects using ML models. This study intends to develop a conceptual framework for employing AI to predict errors in the on-site stage of IHB projects, aiming to support project managers in refining decision-making processes related to project scheduling and planning. This approach not only seeks to bridge the identified research gaps but also to enhance the practical application of AI technologies in improving the efficiency and accuracy of project management in the construction industry.

4 Methodology

The objective of this study is to develop a conceptual framework for the application of AI in predicting and managing assembly errors in IHB projects. This methodology combines a literature review with empirical data gathered from two site visits, eight interviews, and some technical error reports. The focus will be on understanding the practical opportunities and challenges associated with integrating AI into project management practices, rather than developing a predictive model or performing statistical analysis. In this chapter, the research approach, literature review, data collection, data analysis, ethical and sustainable considerations, and limitations will be discussed.

4.1 Research Approach

This study employs an abductive research approach, suitable for exploring such phenomena where new theories may emerge from observed data (Kovács & Spens, 2005; Bell et al., 2019). Abductive reasoning allows for an iterative process between theories and observations, facilitating the development of new insights that neither purely deductive nor inductive methods could achieve on their own (Bell et al., 2019).

In this context, the research began with exploring literature about IHB projects and errors in construction, and to widen the understanding of the processes that are utilized and the production method in the assembly phase. Simultaneously, empirical data was collected through site visits, observations, and initial interviews to widen the understanding of the topic. This enabled the authors to go back and forth to reinforce the study and develop a more concrete and sounding idea (Dubois & Gadde, 2002).

4.2 Literature Review

The literature review conducted for this thesis was designed to lay a robust theoretical foundation, pinpoint research gaps, and ensure the study was contextualized within the set objectives. The review primarily utilized academic search engines such as Google Scholar, Scopus, and the Chalmers University Library. Moreover, IGLC.net was used when exploring papers in the realm of Lean Construction. Additional sources included subject-related academic networks and materials recommended by the supervisor. Recent papers were a priority when conducting the literature review, especially in the realm of error prediction and AI.

In terms of article selection, only literature written in English was considered. Furthermore, most of the chosen articles were published in the European Union, and a significant amount of papers in the realm of IHB are from the Swedish region. As for the topic of AI, the IBM website served as a key reference for defining Artificial Intelligence, aligning with the study's reliance on trusted sources. The literature search employed broad keywords such as 'Construction,' 'Off-site construction,' 'Prefabricated construction,' 'Industrialised house building,' 'Assembly phase,' 'Defects,' 'Errors,' 'Error prediction,' 'Artificial Intelligence,' and 'Machine Learning.' Articles were chosen based on the relevance of their content to the research aims and scope, which was decided by reading the abstract and conclusion of the articles.

4.3 Data Collection

The empirical data was gathered through a combination of qualitative methods to ensure a comprehensive analysis. Below are the data collection methods that were used in the study.

4.3.1 Observations from Site Visits

This research was done in collaboration with Derome Bostad, which is the IHB construction case company for this research. Two site visits to IHB construction sites were carried out to gain a general understanding of the nature of IHB assembly procedures and processes, and to explore the possible issues during the construction stage. As for the location of the sites, one was in Varberg on the 29th of February 2024, and the other was in Kungsbacka on the 7th of March 2024. Both site visits were conducted with the same project manager taking us around the sites, explaining the work processes, and clarifying possible issues. Notes were taken on-site to develop and formulate the case company's workflow.

4.3.2 Interviews

Two of the main types of qualitative interviews were conducted in this research, unstructured and semi-structured (Bell et al., 2019). Since an abductive approach was conducted for this research, unstructured interviews at an early stage were established to gain a wider understanding of IHB companies, AI, and its applicability in the realm of error prediction in construction. On top of that, unstructured interviews allow the interviewee to speak freely about the discussed topic and possibly give a glimpse into certain areas that the researcher might be more interested in asking about (Bell et al., 2019). A total of three candidates were interviewed in an unstructured format.

On the other hand, a total of five qualitative semi-structured interviews were conducted to gain specific knowledge on errors that happen in the construction stage, the possible effects of errors, and their thoughts regarding AI implementation for error prediction in the construction stage. This type of interview allows the researcher to reach the desired topic, which might not be the case in an unstructured interview (Bell et al., 2019). The interview questions for the semi-structured interviews are available in the appendix section. Table 4-1 below shows the interviewees, their roles, their company, the type of interview conducted, and the interview date.

Table 4-1 Interview candidates

Name	Role	Company	Interview Type	Interview Date
Daniel Åkesson	Regionchef Syd	Derome Bostad	Unstructured	Multiple times
Yahia Elsayed	Security DevOps Engineer	Amazon Web Services (AWS)	Unstructured	Multiple times
Johan Brinktell	Regionchef Syd, Bostadsutveckling	Derome Bostad	Unstructured	01/03/2024
Emma Johansson	Projekteringsansvarig	Derome Bostad	Semi-structured	28/03/2024
Vanessa Dubar	Projektledare	Derome Bostad	Semi-structured	28/03/2024
Jianpeng Cao	Post-doc researcher, Specialising in Industrialized construction	Delft University of Technology	Semi-structured	04/04/2024
Patrick Rohner	Construction Manager, International assembly	Blumer Lehmann AG	Semi-structured	11/04/2024

4.3.3 Errors Technical Reports

Several Inspection reports from multiple IHB projects from the case company were collected and explored to understand the nature of data reported on error types, frequencies, and the writing/format style of the documents. The collected inspection reports were on timber IHB projects comprising both small houses and multi-story buildings. Such documents enrich qualitative research as they enable the observers to attain valuable information and understand some background on the case organization (Bell et al., 2019).

Furthermore, the inspection reports were analyzed, and common error types were extracted. The process was conducted taking into consideration the four-eyes principle to achieve a more objective and transparent process (Mark et al., 2003). One of the authors extracted the data, while the other checked the extracted data to ensure and achieve more accurate results (Mark et al., 2003).

4.4 Data Analysis

The research adopted a qualitative approach to analyze the large and unstructured empirical data collected through a case study with an IHB company, a literature review, some error technical reports, and interviews (Bell et al., 2019). This approach was chosen because the research aimed to develop a conceptual framework without the feasibility of conducting extensive empirical testing due to time and material constraints, making a quantitative approach unsuitable.

Thematic analysis was utilized to systematically analyze the data, examining transcripts from unstructured and semi-structured interviews. This method was significant in identifying recurring themes, patterns, insights, similarities, and differences, particularly focusing on the implementation of AI in managing construction errors. According to Bell et al. (2019), thematic analysis provides a framework for processing unstructured qualitative data, ensuring that the insights generated are both comprehensive and relevant to the research objectives.

4.5 Ethical Considerations

According to Bell et al. (2019), there are four main areas of ethical principles essential for conducting research responsibly: avoidance of harm, informed consent, privacy, and preventing deception. In alignment with these principles, this research ensured no physical or psychological harm to participants, with all interactions designed to be safe and respectful. Furthermore, the project strictly adhered to GDPR legislation, emphasizing that no human harm would occur since the study involves only data analysis and research. In the context of informed consent, all participants were aware that the interview would be included in the study and that the study was to be published online, and their consent was given verbally at the beginning of each interview. Finally, the report was sent to the supervisor from the company's side to achieve the final consent before publishing the research.

Privacy was protected in the publication of findings, and sensitive information was securely stored to prevent unauthorized access. Additionally, the company's data was never used in AI online models, respecting their policy regarding the use of AI technology and ensuring data handling met ethical standards. Transparency was maintained throughout the study, avoiding deception by providing participants with clear and truthful information. Adhering to these ethical guidelines protected participants and bolstered the credibility and reliability of the research findings, ensuring the study upheld the highest standards of integrity and respect for individual rights and well-being.

4.6 Limitations

Some limitations of this research are time-based, being six months, thus limiting the authors from further expanding on the subject. Data collected is limited by the project's scope, so technical error reports from the factory stage will not be considered in this thesis. In addition, data collected was from a single case company, Derome, which is not enough to generalize the findings, as further studies might be required. However, to overcome having a single case study, the research is supported with interviews outside the company. It is worth mentioning that there are some other documents, like the variation reports, warranty inspection reports, and customer satisfaction reports, that the company has, which could be included in the report but were not acquired for various reasons. Furthermore, the study is limited by the few errors in the technical reports available.

While exploring and searching for keywords, articles/books were disregarded if they were inaccessible by our university login method or required purchasing to access them. This meant that valuable information might have been inaccessible to the authors. Another limiting factor to exploring the different AI models is the nature of the research being management-oriented rather than technical. All of the aforementioned limitations, along with the company's AI policy, made the testing of an AI application inapplicable in this scope.

5 Case Study

The chapter below will describe the IHB case company Derome, its level of prefabrication, the company's work process, and the observations from the two site visits that were conducted. The text will help assess the requirements and issues when considering AI implementation in IHB companies. The data is collected from the site visits, discussions with Derome's supervisor, and Derome’s website.

5.1 The Case Company

The case company Derome Bostad/Hus is a part of Derome Group, which is responsible for the production of houses. Derome Group has 2300 employees, and their work area consists of supplying wooden/timber elements, selling building elements, renting machinery, producing houses/multi-story buildings, and managing real estate assets. Below are the six main areas that Derome works with (Derome, 2024):

Derome Timber
Derome Bygg & Industri
Derome Träteknik
Derome Hus (includes Varberghus, A-hus, and Plusshus)
Derome Fastighet
Andersson Haus & Dach

Derome Bostad controls the process of building the houses or multi-story buildings from planning to the final step of production, where Derome Fastighet takes over after the delivery of the keys. Derome is an IHB company that mainly builds using prefabricated wooden elements, that are installed/assembled on-site, with some conventional construction taking place (like interior wall cutting and production on-site). However, modular construction is a recent business area that Derome Bostad acquired, but it is still not as stable as the prefabricated element assembly, resulting in more errors at the current time. Table 5-1 shows the classification system of Derome’s IHB systems based on the findings from the theory chapter (section 2.1.2).

This research focuses on prefabricated construction; therefore, site visits and interviews have been conducted for this type of construction. During the site visits, construction sites, methods, and processes have been observed and discussed with the project manager. The projects that were observed had prefabricated structural elements, that were assembled on-site. The assembly rate of the structural prefabricated elements was relatively fast, as it took one day to assemble the structural components in a single-floor house building. The whole process of constructing a single house takes up to 20 weeks, excluding the foundation work. On the other hand, multi-story buildings (up to 7 floors) take up to one week to assemble the structural prefabricated elements.

Table 5-1 Comparing the Case Company's Two Production Methods.

Comparison	Prefabricated Construction	Modularized construction
Classification	Prefabrication & Sub-assembly	Modular Building (Volumetric)
Degree of prefabrication & Pre-assembly	Moderate - Mainly, structural elements are prefabricated.	Highest - The whole module is prefabricated and pre-assembled.
Level of Standardization	Customized Standardization - Some degree of freedom for the customer.	Pure Standardization - Less room for customization.
Construction Time	Structural elements' assembly is fast; however, production on-site for less prefabricated activities can be similar to the conventional construction time.	Relatively fast, as the building comes in modules, eliminating the need for conventional production on-site.
Construction Material	Timber	
Business Start Date	The production of timber houses began in 1975 (Derome, 2018).	Began in 2016 after the acquisition of Plusshus (Derome, 2018).

In the case company, projects are not merely repetitions of previous prototypes. Instead, the company actively considers customer satisfaction reports and market demands before developing new prototypes. This approach is a shift away from pursuing entirely standardized construction methods, aligning with a more responsive and market-oriented development strategy. Usually, new prototypes have more errors in the first units that are produced. However, errors, non-conformances, and variations are noted and solved, resulting in fewer errors in the next units of the project with the same prototype, aligning with the CI lean mentality. When discussing errors, the project manager mentioned that multistory buildings had higher error numbers compared to single-house units due to the lack of experience in these types of projects and the higher numbers of subcontractors.

The construction work process at the case company is done through subcontracting, where all activities on-site are done through subcontractors. From the case company's side, a project leader is responsible for planning and controlling the overall construction site processes and subcontractors. Moreover, the working method in the construction stage is not standardized, as project leaders have the freedom to decide on the working method. On top of that, the company does not have strict rules for documentation and archiving, as every project leader has room for freedom to archive the data in their own manner. In many cases, the subcontractors coordinate together in the project, while the project leader has the responsibility of the overall coordination and control over the project's success. In terms of process monitoring, the company utilizes a checklist to ensure that the processes are completed. However, the time of completion of processes is not registered.

To control the production process, the case company has three main KPIs in terms of, budget which is conducted once each quarter of the project, Customer satisfaction through surveys or reporting errors and follow-up with customers, and Quality KPIs, which are the number of errors that occur in the project, acquired from the inspection report at project delivery. In this context, the company conducts multiple inspection reports per project. The first one is done internally, where the reports are collected before the formal external inspection. This internal inspection is something that the case company does to minimize the errors in the final inspection record, and it is worth mentioning that this inspection is not mandatory. The third type of inspection record is the warranty inspection, which is done after two years of key delivery.

6 Interview Findings

The interviews with various stakeholders involved in IHB projects resulted in valuable insights about assembly stage errors and the implementation of AI within this field. The respondents highlighted various error management practices and discussed the benefits and challenges of using AI in this domain. This chapter presents the key findings from these interviews.

6.1 Common Errors and Their Impact on IHB Projects

When exploring the errors in IHB projects it was clear that error happens in every project, as Cao stated:

> *"In every project, errors occur, but the degree of how often they happen is lower or higher depending on the quality control practices."*
>
> ***Jianpeng Cao***

Patrick further supported this idea and added when discussing the topic of errors, that generally, every ten projects, a project might encounter a huge error with a huge impact and a negative effect on the project in terms of time and budget. However, in other cases, as an estimation, one error happens per room, mainly revolving around scratches or pollution on site.

The interviewees in the study all made similar statements, indicating that errors vary from one project to another and, similarly, the consequences. However, a shared belief between most interviewees is that the final product's quality is not affected by errors in the project. This is because what gets affected by errors are mainly the time and economic aspects of the project as such errors are usually resolved before the handover of the project. On the other hand, one of the interviewees mentioned some errors that require rework after the key delivery to customers, indicating that errors affect the quality of the final product to some degree.

When it comes to common errors, the interviewees had similar insights concerning the number of subcontractors involved in the project, where they all agree that increasing numbers of subcontractors relates to an increased number of errors. The increased number of workers on-site relates to more messiness on the construction site, resulting in more scratches and damage to surfaces like doors and walls. Such errors, although time-consuming, are easy to fix, mainly by painting over the surface or some minor adjustments rather than complete rework. On top of that, issues related to coordination, collaboration, and communication become tougher to manage. For example, this could lead to having different stakeholders, with different versions of the drawing, resulting in mismatches and problems in the construction stage.

One area where more errors are known to happen is the new prototypes, this is because there is a lack of knowledge for the stakeholders involved in the project on this new design of the building, resulting in new errors that can be uniquely attributed to this prototype. Further complications can arise if the project leaders are not informed of the new errors when they first come up. The main reason for the project leaders' lack of awareness, is that some subcontractors try to fix the errors on the spot, thus breaking the loop of CI efforts in projects.

When it comes to design errors, these happen not only in new prototypes but in some cases, miscommunication, incorrect interpretation of deliverables, and lack of synchronization between the factory and the team on-site can cause errors, especially with increasing numbers of subcontractors involved in the project. These types of errors might not be as common; however, the effects of such errors can be huge, especially if they require rework of some critical prefabricated elements (due to quality issues). This can result in intensified delays and budget overruns.

An example was provided of such design errors, where MEP openings are integrated into the prefabricated element and the drawing mismatches with the one executed on-site. Such errors can sometimes be solved with minor adjustments, creating a new opening in the prefabricated wall in another location and fixing the open hole. This design error primarily happened due to the lack of coordination, as the design was done by the main contractor, and the subcontractor on site was not the same person in charge due to changes in the design.

Interestingly, time itself is both a reason for errors and an effect of errors. Time can be a reason for error if the project has timeframe limitations, as this adds stress to the project's stakeholders, pushing them to deliver at a faster pace; this was mentioned by the interviewees as harmful to the project, leading to a higher error count. On the contrary, errors result in rework, delays, or adjustments, all of which relate to additional time spent on the project for some or all of the project's stakeholders when errors happen.

On a similar matter related to time, the logistical delays that happen (not so often), can have detrimental effects on the projects, especially when some IHB companies employ JIT methods with material management. Having materials arrive late to the assembly site can result in idle time for the people working, the rented equipment, and other issues making this a serious problem with a high impact on the project's timeline.

Ultimately, the biggest problem with errors is that errors have a domino effect stapling over each other since errors can lead to other issues, as Patrick said:

> *"The later the error is discovered the more effect it has on time, cost, and quality."*
>
> ***Patrick Rohner***

For example, if there is a problem with the waterproofing of a certain area, the water can leak into other components, and then even the structural components might need changing, causing extra work and waste.

Finally, customer satisfaction is crucial for IHB construction companies. This is why the lower the error count in the inspection report, the better for the IHB company's reputation. This is because the handover inspection report is something that the client will see and base his impression upon.

6.2 Current Error Management Practices (EMP)

Tracking and assessing project performance is essential for project success. However, the uniqueness of projects in the construction industry is a limiting factor. This is why IHB companies rely on different KPIs to better assess project performance. When it comes to the relation of KPIs to errors, error management practices (EMP) might be crucial to maintaining adequate quality levels in the assembly phase.

EMP in the IHB companies seems to vary from one project leader to another; however, some key practices were common. To have a clear understanding of the EMPs, KPIs in the IHB companies were first discussed. KPIs are good indicators for companies to assess that the errors are controlled to some degree; however, KPIs might not have a straight connection to error mitigation. This study discussed KPIs related to the economy, time, quality, and production rate.

Patrick stated that production rates, such as modules installed per day and square meters per day, concerning prefabrication assembly are some of the ways that IHB companies measure productivity. They utilize experience and estimations from previous projects to estimate the productivity levels needed to be on track in the current projects. To assess quality, they conduct multiple quality control checks as an in-house inspection method throughout the project's timeline. The quality control checks are performed after the completion of each part of the project, like a room, an apartment, or even a floor, such inspections help the company by making sure that the finished product's errors are solved throughout the project and not only at the end of the project when the handover inspection is conducted.

Similarly, the case company conducts in-house inspections, which they call control inspections, which are also conducted for similar reasons to minimize the error counts before the handover inspection. However, Vanessa takes this approach even further, by performing personal quality controls before the control inspection, thus minimizing the errors further. She estimates that her method helps minimize the error count to reach up to three errors in the handover inspection. Her method helps her come closer to the company's aim of zero project errors. This is why the company measures the error count in every project as one of the KPIs.

As for other KPIs, quality improvements, and performance measures in the case company, variation reports are done for every project, where the project leaders register the noted variations/non-conformances in the project aiming to achieve CI. However, the reports are not done in a standardized format, meaning that the quality of each report depends on the method and accuracy that each project leader adapts to record the variations. The variations are then discussed after the completion of the project in a meeting format with other project managers.

Another KPI report that the company uses is the customer satisfaction index, which is performed by a third party responsible for gathering the satisfaction report from the customers. The last quality improvement report that the company performs is the operational improvement report, where the suggestions, learnings, and findings from the current year are analyzed and reported in hopes of CI. This type of document could include measuring what needs to be done, changing processes, or adding extra text in documents to make the next projects/inspections safer.

Although delays occur due to errors, the case company interviewees stated that the project's lead time is rarely affected. This is mainly due to the company giving the project a longer timeline, as they include an estimated error handling time in their time plan schedule. Much of the schedule time planning is based on the previous project’s timeline, while decision-making is based on experience and teamwork within the team, rather than the reliance on historical data analysis.

When new construction prototypes are produced, project leaders collect errors and variations and share them with the project’s team to prevent errors from happening on the next project with the same prototype. In this case, it is mostly feedback concerning minor design changes that prevent errors from happening. In efforts to prevent most of the aforementioned errors, the design team focuses on clash detection techniques early in the design phase, which is where the use of tools like Bluebeam in meetings with project stakeholders proves beneficial.

Other tools, other than Bluebeam and clash detection tools, are utilized to control the project’s success. For example, a common tool that is widely utilized is MS Excel, which is mainly used in IHB companies to document data about projects. Historical project data in Excel sheets are sometimes used to estimate similar projects. However, there are some limitations to Excel sheets regarding unique projects with little resemblance to older projects.

To solve some of the deviations that happen in projects, Cao states that synchronization between the factory and the on-site production team is essential to solve the logistical issues and ensure managing the deviation most efficiently. A tool that can help in this manner is the Digital Twin, which can offer real-time information-sharing capabilities between the site and the factory. He explains that when deviation or errors are not synchronized properly, the after-effects intensify, costing the project more than needed in terms of time and cost.

Involving subcontractors, workers, and other stakeholders in earlier stages of the projects is another method that was mentioned to lower or mitigate errors in the project. This method is beneficial in this regard because it combines the knowledge and experience from all trades on the project to have the best possible planning for the project. Such meetings are beneficial not only for the mitigation of errors but also for lowering costs and enhancing the project timeline.

Other than the early engagement of the subcontractors and the workers, Vanessa explained that she likes to communicate the importance of limiting the errors and potential rework of the project, indicating to them that rework after the completion of the project will result in more costs and loss of time for their subcontracting company. To further foster collaborative nature and teamwork, she also celebrates projects with the team members of the projects that had low error counts. Similarly, other project leaders in the company employ some incentives to engage the team and lift their morals in contributing positively.

The case company also works on a subcontractor evaluation system to assess which subcontractors usually have the lowest errors possible. This evaluation is usually the basis for team selection of new projects, making quality one of the priorities of the subcontractors to ensure being selected in new projects. This also helps the company in building long-term relationships with some of the subcontractors, providing benefits for the subcontractors by having future possible work opportunities (if quality is kept adequate) and for the case company, ensuring having a team that is well equipped with previous knowledge on the assembly processes used.

Another method that was mentioned to minimize the possibility of errors happening in projects and their impacts in a proactive manner is the implementation of a pre-job debriefing and a risk management system. The risk management system can be used to assess and analyze the risks that come with projects and plan appropriately to avoid them. However, the risks in this situation are not limited to errors but include other types of risks, economic risks, safety risks, and other risks.

Other than these tools and methodologies, some IHB companies develop best practice booklets, intending to limit deviations and create the most optimum method of assembly. Theoretically, this might be a good solution to maintain adequate quality, minimize errors, enable a safer environment, and minimize waste. However, the reality is that the usage of such best practice booklets is not compulsory, limiting the number of workers utilizing them.

6.3 AI Implementation in Projects from an IHB Point of View

Interviewee respondents indicated that they are not aware of any implementation of an AI tool for predicting errors in the assembly/construction stage. However, one of the interviewees did state that some innovative studies have been performed in the realm of visualization and AI, utilizing AR helmets to assist in the construction stage and limit the errors on-site.

The potential for innovation in IHB companies seems to be higher than in conventional construction companies, this can be attributed to the fact that IHB companies are more industrialized. The main difference is in the approach of IHB companies, as their methods have higher levels of digitalization and standardization. Moreover, IHB companies are more centralized and, in many cases, have control over the whole process of construction projects, ranging from the supply of materials to the final stage of constructing the buildings.

As for the most appropriate areas of AI implementation, interviewees offered different insights on AI being a good tool for contract purposes, reviewing drawings in the design phase, planning and scheduling of production processes, maintenance prediction for construction tools and equipment, and in facility management, to help in maintenance prediction. When asked about the usage of AI in the prediction of errors, respondents indicated that this implementation could provide a beneficial outcome for the project leaders in terms of assistance, estimation, and decision-making purposes.

When it comes to the prediction of errors with the help of AI, respondents were asked about attributes and features of the construction that can be a useful input in the AI models, where most of the respondents indicated that historical records like inspection records can be utilized. One of the respondents added more on the topic, listing some other features, like product features and specifications, geometry, material, building system itself (the prototype used), and the structural system of the building are all important aspects or attributes to be included in the model.

Finally, the respondents are aware that historical data of previous projects is of great importance but will require heavy manual work for it to be utilized. This is where AI comes into the picture, but as Cao said:

> *"AI usability in construction is not a new idea. However, how to make the AI model expandable and interpretational, basically opening the black box, is the challenge; making it more trustworthy and making people trust the AI tool are all challenges that face AI. These challenges need to be addressed before AI can be more usable in the industry."*
>
> ***Jianpeng Cao***

6.4 Technical Implementation of AI for Prediction of Errors

The findings in this sub-section primarily came from unstructured and repetitive interviews with Yahia, who has a background in computer security and computer science. When asked about what areas AI specifically could help with, he answered:

> *"AI can be employed to eliminate manual and time-consuming repetitive tasks, which saves time and allows us to focus on more creative and complex aspects of our work."*
>
> ***Yahia Elsayed***

Further implementations of AI are possible, ML specifically can help by learning from data sets to understand the pattern in data. This type of learning, which is a subset of ML, can be both supervised or unsupervised depending on the task needs of the user. The main advantage of supervised learning is that the user wants to see the relation between different data sets without the need for DL (unsupervised learning) that can further find hidden patterns that the user is unaware of.

Both methods are useful, but each uses different computational techniques. However, some of the supervised techniques that can be used for prediction and estimation utilize models, like Linear Regression, Random Forest Regression, and gradient-boosting regression. These tools have different accuracies depending on the data at hand. This is why ML models need to be taught around 70% to 80% of the dataset and then tested with the remaining to measure the most adequate model for the task. However, the percentage of data that the model needs to be taught with depends on one case to another.

This is how prediction, in simple terms, can be conducted, but before that, there is the need for data preparation, which was explained shortly in the interviews. NLP is an ML technique that has many implementations with linguistical applications, like language translation and text summarization. However, in this case, NLP can be utilized by providing the model with human language data to learn from, aiming to teach the model, about some of the abilities that humans have in the linguistical capabilities. For example, concerning construction reports, the model can learn that scratches on walls or damage to walls both mean the same thing, which could be damage to surfaces. Similarly, the model will require both testing and choosing an appropriate model to adapt to the project at hand.

Finally, although AI is beneficial, it is important to note that its accuracy is not 100% as it is a prediction and not an accurate calculator. This means that the final decision is in the hands of the project manager, and AI tools are merely assisting tools to help the project managers, not fully relying on them.

6.5 Potential Benefits & Challenges of AI Integration

AI tools are seen to have multiple benefits in the IHB companies, as the respondents provided positive thoughts concerning how AI could help. Some respondents thought the summarization and analysis capabilities of huge data could greatly help project leaders, especially since this removes or assists in some of the administrative tasks that the project leaders are responsible for. AI could help them by ensuring that all parts of a certain task are done, or maybe help in discussing important aspects of a new project. Another area of analysis relates to analyzing previous projects to provide insights to the project leaders to understand what went wrong in the project and communicate it in a way understandable to the project leaders.

Data management might be the biggest challenge that faces the IHB companies according to the respondents. These companies usually have huge amounts of unstructured data that require preprocessing to be useful and a small amount of structured data. As Vanessa said:

> *"When it comes to data, there is little data to learn from as of now, so the first step is that data needs to be organized correctly."*
>
> ***Vanessa Dubar***

In addition, in some cases, even the manual heavy work of preprocessing might not be enough as the data entry is not of good quality, adding to the challenges of data management. Such challenges, if not resolved, will result in project managers' negligence towards AI techniques, as the initial investment in AI might seem too high in terms of time or cost.

To address some of the challenges regarding data management, AI's NLP can help, as the tool learns from the historical human language data to predict patterns and relations between words and sentences, thus enabling the automotive approach of the classification of data into generic ones. For example, Daniel mentioned that project leaders usually spend much of their time on administrative work, like reading inspection reports and specifying who is responsible for fixing the errors in the inspection records. In such situations, AI tools can help by understanding the written errors, classifying them into generic ones, and even proposing who is responsible for fixing them.

Some of the interviewees are skeptical about implementing AI in less standardized and prefabricated processes. One thought AI tools might be more applicable to modular construction, as it is far more standardized and less complex, making the AI application easier as an initial step. Other than that, there is the fear of the unknown, like possible scenarios in the future where the tool might become unstable. Such skepticism of the tool and other factors intensifies the resistance to change, creating barriers to AI implementation in the construction industry. One of the respondents believes that the construction industry is reluctant to accept new technologies and knowledge, stating that this is because of the industry's conservative nature. Other respondents did not share the same idea but do consider AI to be a big jump to take.

7 Analysis

This Chapter employs thematic analysis to answer the research questions and develop the conceptual framework. The chosen themes are common errors and their impact, existing error management practices, attributes and characteristics of IHB projects, the potential of AI for error prediction in IHB, and the proposed conceptual framework.

7.1 Common Errors and Their Impact

The literature review and interview study identified several common errors in IHB and their impacts. The findings from the literature focused on the documented errors in inspection reports, including handover and post-handover inspections. However, the interview study presents errors from respondents' experiences across various projects, many of which remain undocumented. When it comes to the case company, errors in control (construction), and final inspection reports for nine different buildings have been analyzed. The analysis is done to align with the classification of errors in terms of type, considering the literature review findings, especially Johnson and Meiling (2009), Macarulla et al. (2013), and Forcada et al. (2015). A total of 333 errors identified in these reports were organized into 11 distinct categories, as illustrated in Figure 7-1.

On average, each building exhibited approximately 30 errors, consistent with interview revelations. Noteworthy is one building with over 90 documented errors, which indicates several damages in different components. The distribution of error types in inspection reports highlights that the most common errors were Missing (26%), damage (18%), misalignment (12%), and issues with surface appearance (11%). These findings support earlier studies, which noted that such errors frequently occur. Moreover, missing elements, surface appearance, and damage errors are often correlated with the number of subcontractors involved, potentially leading to a chaotic construction site and subsequent defects like scratches and damages. Although these types of errors can be resolved simply, they cost companies additional cost, time, and effort.

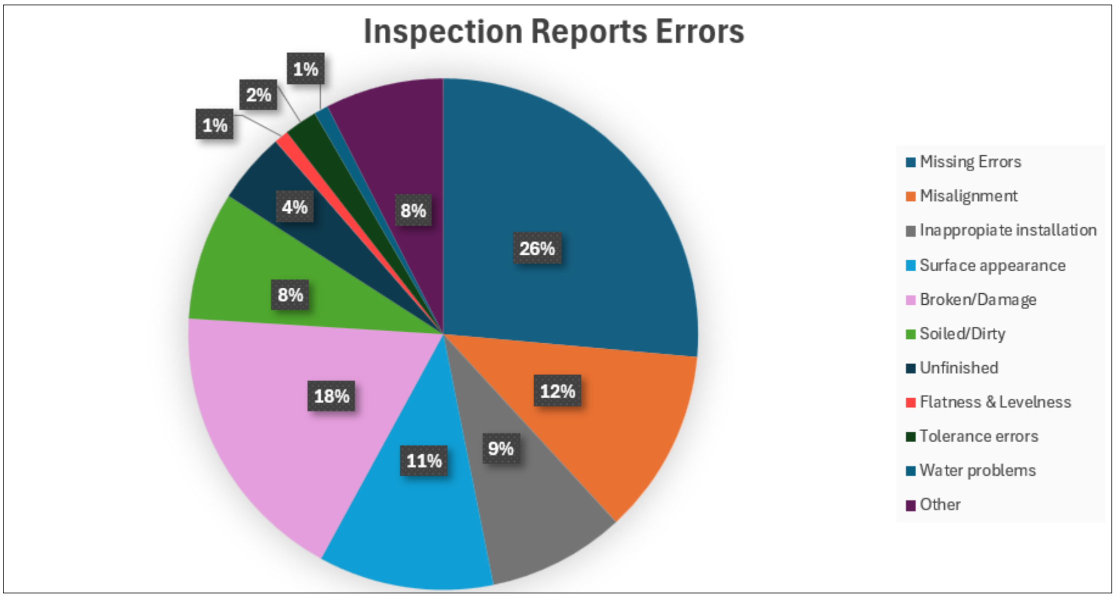

Figure 7-1 Most common errors for the studied inspection reports.

According to the literature findings, misalignment and inappropriate installations are often attributed to substandard craftsmanship, impacting the overall quality of the final product by introducing issues like installation gaps and incorrect measurements, which were clearly shown in the inspection reports. Furthermore, errors categorized as unfinished in the control inspections generally relate to ongoing construction activities that were not completed at the time of inspection. However, some of them have still not been completed in the final inspection. In some cases, the inspector mentioned that the cause of unfinished work could be because of uncontrollable events, such as weather conditions, which resulted in delays. Usually, these types of errors necessitate post-occupancy reworks, thereby affecting customer satisfaction, as highlighted by the literature and by one of the interviewees. On the other hand, it is noteworthy that only 16 errors existed in the final inspection in the final inspection of the 9 houses, which means that most issues are resolved prior to handover. This result is supported by interview findings indicating that these errors generally do not compromise the final product quality since most of the errors are resolved before the handover.

Design-related errors emerged clearly in the interview findings, while they were not clearly indicated in the literature or the inspection reports. However, such errors often remain undetected until execution and are primarily linked to different types of errors that appeared in the inspection reports, such as tolerance errors, including discrepancies in measurements, affecting the functionality of certain building elements. These issues stem from inadequate communication during the design phase and poor coordination in the distribution of design versions among stakeholders. Design errors are not specifically listed in the inspection records because the inspector cannot be certain of the cause of a certain error.

One of the repetitive types of errors conducted in the final inspection reports was the mismatch and incorrect colors used for certain elements, which usually related to elements that the customer can customize, this can be interpreted by the room of customization and the standardization level that the company follows to achieve the customer need as mentioned in the interviews. This room of customization can cause these types of errors, especially when the project contains the same prototype and the same subcontractors involved but with different customization, which is the case in the collected inspection reports. In this context, other repetitive errors from one building to another can also be interpreted by utilizing the same subcontractors for the same project as well, and it can be related to design errors such as tolerance errors, as mentioned above, where buildings have the same prototype.

Comparing analysis of the literature and inspection findings in terms of the most common elements subjected to errors shows alignment, particularly in the prevalence of errors concerning wall and window elements, ranging from minor surface scratches to more significant damages. In the context of walls, although the interviews and literature mentioned common errors concerning wall openings and HVAC systems, these were less evident in the inspection reports; possibly, it can be interpreted by the internal walls and their openings being constructed on-site in the case company.

It is crucial to note that inspection reports typically only document inspected errors, thus not encompassing all on-site errors. For instance, these reports often omit logistical problems mentioned in interviews, which cause delays and escalate costs. The interviewees mentioned that such problems have a huge impact on projects. The errors that do occur due to such problems could lead to further implications, like increasing idle time in the project.

The consequences of errors are manifold, including increased costs, time delays, necessary re-works, and impacts on customer satisfaction and company reputation, as consistently repeated in both interviews and the literature. However, the psychological stress and impact on the customer due to the late rework was one of the exceptional literature findings. Additionally, a unique insight from interview findings supported by the analysis of inspection reports is the domino effect of errors; many issues are precipitated by preceding errors or omissions, with subsequent installation problems if these initial errors are not rectified.

7.2 Existing Error Management Practices (EMP) in IHB

In IHB construction companies, multiple planning activities and practices are utilized to ensure the project's success in terms of scope, time, and cost. Although many of these practices are not specifically oriented to address errors emerging in the assembly stage, many offer solutions to these errors. For example, Lean's principles focus on waste reduction, variation reduction, and increasing prediction in projects, all of which help projects control and minimize the room for errors.

A common technique utilized to achieve some of Lean's aims is the LPS, which aims to minimize project variability. To achieve that, for example, LPS's PPC metric is used. This metric allows project leaders to avoid missing steps and ensure the completion of the plan as a whole. This metric helps to minimize errors of the type "missing," which occurs when tasks are not completed.

However, PPC does not help when mitigating other types of errors that relate to quality, which is why quality control measures and CI are critical to ensure that the project deliverables achieve high standards. Unlike the reactive approach when dealing with challenges, CI aims to ensure the development continuously from one project to another; this incremental approach, if established properly alongside standardization, could enable IHB companies to minimize or prevent errors that always occur in the assembly stage.

When discussing CI, similar concepts emerge, such as PDCA, RCA, and mistake proofing, all of which aim to study a specific problem/challenge and further analyze it. RCA, one of the Lean techniques, aims to find the main reason or root cause of the problem at hand. PDCA shares the same idea as RCA, by studying the cause of a problem, but takes the approach even further by implementing different strategies to deal with the problem at hand and finally standardizing the most adequate solution. On the other hand, mistake-proofing aims to prevent the error/problem by placing a step/device that does not allow the error.

An example of a mistake-proofing tool would be augmented reality glasses that guide the workers in the assembly process and ensure the completion of a certain process by showing the errors when they happen, thus alerting the workers of them in a predictive manner before the inspection stage. Although PDCA, RCA, and mistake-proofing are beneficial for IHB construction companies, the implementation of such methods remains low, mainly due to the high investment needed.

Similarly, the utilization of other production methods, like dividing the project into smaller modular components, can minimize the errors by up to 50%, however, just like the previous methods, this is not easily achievable, as this requires a high degree of standardization, a thing that might not be achievable for some IHB companies, due to the client's needs for customization. However, new technologies like AI and data analysis techniques have been conducted to ensure better project predictability of errors, delays, and cost impacts. The usage of AI has increased in the construction industry, yet mostly in stages before the assembly stage, mainly focusing on cost and delays.

Furthermore, most studies relating to new technologies are experimental, and practical implementations of such tools remain limited. For example, the use of the Digital Twin is discussed as having huge benefits for synchronization purposes between the factory and the site. The increased synchronization is reported to have a huge impact on minimizing the effects of errors, this is because reporting the error to the factory when it first happens in a real-time manner can reduce the stapling effect of errors on each other.

However, IHB companies have been using other alternative approaches to address errors that arise in projects. One of the most common EMP conducted by IHB companies is project inspections. Although inspections are often obligatory, IHB companies are aware of the benefits of inspections, which is why they conduct control inspections before the mandatory inspections. Some project leaders take this approach even further by conducting their own inspections prior to the control inspection stage to ensure a lower error count.

Limiting errors in projects is one way to increase customer satisfaction, which is why some IHB companies track error counts as one of the main KPIs in the assembly stage. Other types of in-house documentation are conducted to achieve CI. For example, variation reports are conducted to report the nonconformances and errors that are noticed in the projects. Another example of in-house documentation for CI purposes is the operational improvement report, where new solutions, ideas, or changes are noted on a yearly basis. However, IHB companies might also conduct documentation through a third party. The case company, for example, keeps track of the customer satisfaction index, which is obtained by the survey sent to the customers, and the errors that happen during the warranty period.

Other than documentation after the project's completion, IHB companies address the EMP with other methods, like project planning. This is where rework and delays due to errors are considered in the planning and scheduling stage. Project leaders utilize their experience to estimate the impact of the errors on the project, and in some cases, documents of similar projects are utilized for estimation purposes. Nonetheless, historical data usage remains scarce due to the limitations of data being documented in inadequate formats for further utilization. The documentation problem grows if the companies do not have a standardized format for archiving.

Planning for the assembly stage is not only related to the timeline, but as a pre-job, debriefing and a risk management system are some of the planning strategies that can help assess the project and enable the project team to have better control over errors. In this stage of planning, early engagement of subcontractors and different stakeholders in the project can have additional benefits. Early engagement with subcontractors can be utilized to share experience, knowledge, and understanding of the assembly processes to develop a better plan with a higher chance of minimizing errors. The early engagement suggests that the management of subcontractors is essential for the success of IHB companies.

When it comes to subcontractors, some IHB companies offer best practice booklets to workers who might not be delivering adequate levels of quality. The usage of such booklets is mostly nonmandatory, but it has been discussed as having a positive effect on the projects. Other than manuals, some IHB companies utilize incentives like a celebration or prizes given to the team with the lowest error count as a way to inspire subcontractors to perform better.

Further methods are also employed to ensure high quality from the subcontractors. Some IHB companies utilize a subcontractor evaluation system to assess the quality of work (for example, by checking for the error count), time assessment (assessing the delays due to the subcontractor), and cost (checking for cost-related issues due to the subcontractors). This evaluation type helps the company decide which subcontractors are best fit for future projects. On top of that, subcontractors might be more willing to cooperate to ensure that they are chosen for future projects.

7.3 7.3 Attributes and Characteristics of Projects to Be Included in the AI Tool

Errors and defect profiles change in terms of their impact and magnitude due to some project attributes and characteristics. Insights derived from both literature and interviews have identified key attributes that should be considered while analyzing different errors and conceptualizing an AI tool.

Firstly, project-specific characteristics play a crucial role in determining the types and frequencies of errors encountered. The literature has identified attributes such as floor area, number of rooms, number of stories, type of buildings, and overall project complexity as critical factors influencing error profiles. Complexity, often linked to the type of building prototype used, particularly affects error occurrences. Projects utilizing new prototypes are subjected to unique and new errors. As errors are reduced with repeated use of the same designs, teams gain experience, as highlighted by one of the case company respondents. Moreover, the level of standardization and customization utilized in the projects also affects error likelihood and types, as previously mentioned. Customized projects tend to have more errors than standardized projects, where repetitive processes help reduce error occurrence over time. Moreover, the level of prefabrication, for example, the inner walls, as mentioned before, sometimes prefabricated elements can be subjected to errors more than the constructed on-site, especially the openings in the walls.

Craftsmanship quality, particularly the expertise and experience of subcontractors involved, is a significant factor in errors. The relationship between subcontractors and the main construction company and the number of subcontractors engaged correlate with the frequency of errors. Increased numbers of subcontractors often lead to a messy construction environment, increasing the number of errors.

On the other side, project management dynamics, including the managerial team's experience and efficiency, are highlighted in the literature as one of the essential attributes. The project leaders and their experiences in IHB projects can affect the occurrence and magnitude of errors.

Temporal factors, such as project duration and specific timelines, are also crucial. Tight timelines can increase stakeholder stress levels, resulting in a higher probability of errors. Including these temporal aspects in AI models helps predict when and where stress-induced errors might occur. Finally, external factors like weather conditions, though less predictable, were one of the attributes that affected the occurrence of errors. These types of attributes are characterized as unpredictable due to their nature.

Table 7-1 Summary of Errors-influencing Attributes
Floor area
Number of rooms
Number of stories
Type of buildings
Building prototype
Level of standardization
Level of prefabrication
subcontractors company name
Years of experience of subcontractors in IHB
The Relationship duration between subcontractors and the main construction company
Number of subcontractors engaged
Project Leader
Years of experience of project leaders in IHB projects
Project duration
External Factors

7.4 Potential of AI for Error Prediction in IHB

AI has many potential benefits for IHB companies and the construction sector in general. The industry's needs and shortcomings need to be discussed to address these benefits. First, the construction industry relies heavily on project leaders' experience in decision-making. Although the experience of project leaders is a great asset, there is a huge amount of data in the construction industry that can be beneficial. For example, AI can help project leaders in estimating and predicting a certain aspect of the project based on the data input like historical records of projects. Such usage can aid the project leaders and the planning team especially when combined with other previous techniques like the CPM and the LPS. AI tools can be used to rapidly analyze a huge amount of data for the planning purposes of the LPS, making the processing time shorter than traditionally required.

Second, time is critically important in construction projects, as workers, specialized project managers, and large equipment cost the project heavily. On top of that, the construction sector’s profit margin is lower than that of other sectors, further proving the importance of the time aspect. This is why AI tools can be beneficial in reducing the time taken on some tasks, especially for many of the project leaders’ administrative tasks. AI tools can help in many areas, like estimation purposes, providing project leaders with a fast prediction/estimation of a certain task and data entry in an automated way, enhancing the digitization processes, and leading to time savings for the project.

Third, the benefits of AI are not limited to time, in fact, quality is another area that AI can help with. An example is unsupervised learning, which can be performed for prediction purposes, giving insights into significant factors that could affect the project.

Such insight can be beneficial for project leaders, enabling them to see hidden patterns that might be difficult to analyze otherwise. For example, the AI tool could indicate that a certain attribute/feature of the project has the highest impact on the project, this is where the project leader's experience can be input to further study the matter. Other than data analysis, AI, combined with other technologies like cameras, can provide real-time vision-based methods that help ensure the quality of the on-site work.

Fourth, the construction sector has problems regarding data management. For example, most material handling processes are done manually, on paper, or in a PDF file; such traditional techniques are time-consuming, increase the risk of human error, and cause data loss. Further intensifying the issue is the unstructured data and the lack of proper documentation, where data is documented without a standardized procedure. AI tools can be beneficial in such situations, helping in the automation of data processing. ML techniques like NLP can help by learning the human writing style/format to understand to some degree what a certain sentence/phrase means and then writing the sentence in a standardized format.

Finally, many studies prove that AI's implementation for prediction purposes was highly accurate, anywhere between 70% and 90%. Such a high degree of accuracy in prediction/ estimation can be combined with project leaders' insights, to provide beneficial outcomes for the project management's team. Many of those studies mainly utilized regression ML models to predict delays, rework causation, and cost estimation in construction projects.

As for some of the challenges facing AI's implementation, some errors revolve around resistance to change. People tend to oppose new ideas, especially since AI is an idea that some people are skeptical about and think that it might take their role in the future. Others see AI as a high initial cost and might not be inclined to add it to their company's practices, just like BIM is with some companies. Further spreading the knowledge about AI's capabilities, benefits, and practical implications is essential for the industry to accept AI.

Another key challenge that needs to be addressed for better implementation of AI relates to the prior challenge of data management. It is clear from this research that in many areas, the construction industry does not document what is happening or, in some cases, documents some aspects and leaves others, limiting the CI process and negatively affecting AI's data necessities. One example is how subcontractors or construction workers might fix errors that arise in the project without documenting or reporting the error to the management team, or not documenting the time of task completion in the project. These issues limit the usability and accuracy of the AI models, depending on the area of implementation.

To conclude, from the construction industry, IHB companies are the most promising for AI implementation, as they are more accepting of innovative ideas. IHB is similar to industrialization in other sectors, such as the manufacturing and automotive sectors. The IHB companies are generally more standardized, digitalized, centralized, and less fragmented than conventional construction companies, providing better AI implementation capabilities.

7.5 The Proposed Framework for AI Implementation

Based on the findings of this research, a conceptual framework for an AI tool for predicting errors in the assembly stage of IHB construction projects is proposed in this section. The conceptual framework will delve into some of the main steps, beginning with data collection and ending with model refinement. Figure 7-2 below provides a flowchart of the proposed conceptual framework, including all the necessary steps. The tool's interaction with IHB managerial practices will be discussed in the discussion part later.

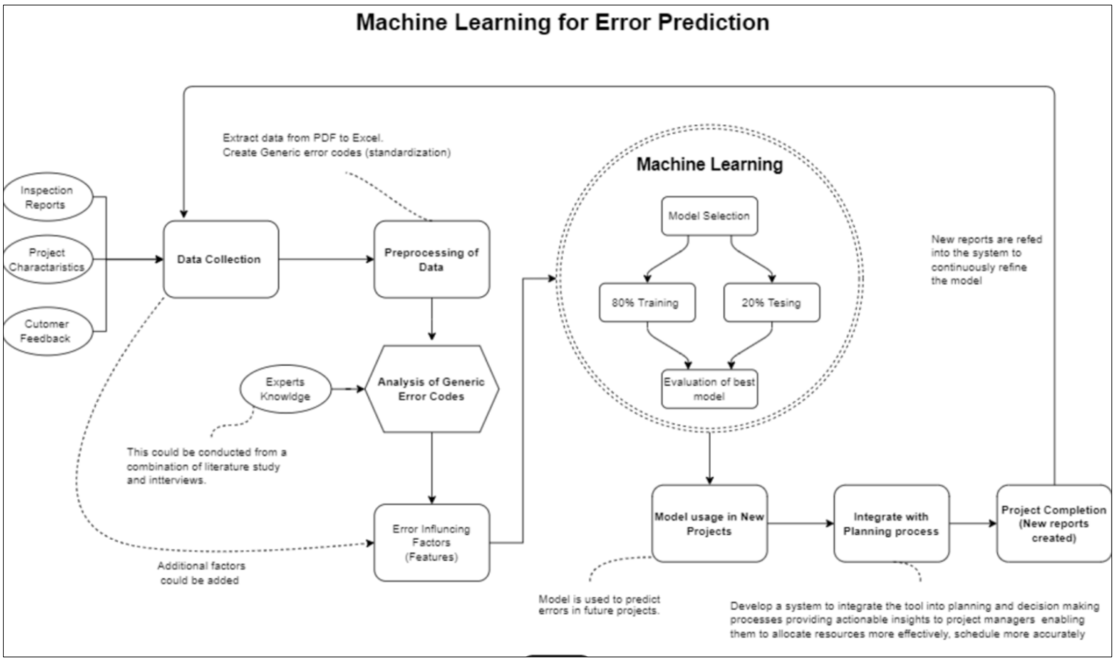

Figure 7-2 A conceptual framework of an AI prediction tool for the assembly stage in IHB construction projects.

7.5.1 Data Collection

The first process in the proposed framework is data collection. In this step, collecting all relevant data associated with errors in the assembly stage of the IHB projects is essential. Data associated with errors can include the errors that happen in projects, the characteristics and features of the project, the factors that affect errors, and the stakeholders involved in the project. Such data can be mostly collected from historical archives; for example, inspection records and customer satisfaction and claim records could provide insight into the errors that occurred during the assembly stage. Another type of historical data is the archived variation reports, where non-conformances and new errors are recorded from the assembly stage. This is where insight into the causation of error can be derived from, as such reports can have some insights into the variations and not only the errors themselves.

In Sweden, three types of construction project inspection audits are usually conducted: control inspection, handover inspection, and warranty inspection. The audit process can vary from one company to another, or from one inspector to another, creating a challenge when processing and extracting the audits into a generic format. Furthermore, the audits are documented in different styles, where some inspection companies utilize table formats, and others utilize a listing format, creating a challenge for an autonomous AI extraction tool.

Other types of documents that provide insight into the project's features and characteristics are also necessary for the AI tool. This type of data can be the basis on which the AI tool will depend to provide prediction. For example, the AI tool could utilize information about the project's subcontractors count and find correlating trends that show an increase in error count when there is an increased number of subcontractors involved in the project. The error-influencing attributes are mentioned above in sub-section 7.3, providing initial attributes to be included in the proposed framework.

7.5.2 Preprocessing of Data

The second step in the proposed framework is data preprocessing, which might be the biggest challenge at the beginning of the proposed framework. The main reason for this issue is the construction sector's lack of proper documentation. For example, most of the data available in the inspection record is written without following specific standards. When it comes to other types of documents like the variation's reports, each project leader reports the errors/variations in their own style. On top of that, some data might not be documented if the project leader does not see the need for it. Proper documentation is required to overcome the aforementioned challenges. For the AI model to utilize errors, they must be extracted and classified into generic error codes. Below are insights on how this step can be conducted.

7.5.2.1 Generic Error Codes

As specified above, generic error codes are required for the AI tool to predict and draw trends from historical data. For this purpose, beginning with the classification system of the errors from the inspection reports can be suitable for preprocessing the data needed for the proposed framework. In this research, a preliminary classification was conducted to categorize the errors based on error type. The next step towards developing robust generic error codes will require further analysis and classification of assembly errors, combined with expert knowledge in the realm of IHB. The generic error-coding system can be similar in form to Park and Seo's (2021) classification (refer to Appendix B) but directed in its approach to IHB projects in Sweden.

7.5.2.2 Error-Influencing Attributes

Similar to the generic error codes, the characteristics of the project and the building are essential for the AI model. This is because the AI tool will depend on drawing trends between the project attributes and the correlating errors, thus predicting errors in future projects based on similarities between projects. This is why the extraction of the attributes in a structured manner to a CSV or XLS file format will be necessary for the AI model to utilize. An initial characterization of error-influencing attributes has been conducted and provided in Table 7-1 of subsection 7.3, serving as a preliminary input format for the conceptual framework.

7.5.3 Automated Data Extraction

After developing the generic error codes and the error-influencing attributes, the next step is to extract the errors and the error-influencing factors into a separate XLS or CSV file format for the AI to utilize. However, manual data extraction is inefficient as it is time-consuming and will have to be done for every project. These challenges create a need for an automated extraction method to avoid intensive and manual work. For this purpose, an automated extraction tool that can deal with the various human language styles is required to understand the different writing methods.

NLP models can be utilized to help with the aforementioned challenge. The model can be taught human phrases/sentences linked to a specific generic error code. For example, error code A1 could mean a scratch on the wall that requires repainting, however, this could be documented in different ways in the historical records, like a ‘scratch on the wall,’ ‘repainting needed,’ or ‘painting issues,’ where all mean the same thing and to be categorized as A1. After teaching the model, automation will be achievable with the help of the NLP model and other extraction tools.

7.5.4 ML Prediction Model

After having a structured CSV or XLS file with all the errors and error-influencing attributes documented in a structured way, the next step is inputting the data into a predictive model that is most appropriate. However, there are two main types of AI learning that can be utilized: supervised and unsupervised, each with its own benefits and different usage.

Utilizing supervised learning can help in predicting errors in the IHB assembly stage, especially after achieving a structured dataset from the previous step. An example of a supervised ML model that can predict the probability of an error happening is Logistic Regression. This is due to its ability to handle binary classification problems (error occurrence coded as "yes" or "no") and predict the probability of an event between 0 (no chance) and 1 (certain chance) (IBM, 2024). However, in the case where a certain error can occur multiple times in a certain project, different regression models like the Linear Regression models might be more appropriate as the Linear Regression model can provide a relationship between error percentage and the error-influencing attributes.

Deciding on an appropriate ML model that best fits the use case and provides the probability of errors happening in projects requires testing. A common practice of testing with datasets is to split the data into training (80%) and testing (20%) sets. The training aims to allow the model to learn the relationships between error-influencing attributes and their occurrences. Once trained, the model's performance is evaluated on the testing dataset. This ensures that the model will function well when predicting errors in future projects and avoids overfitting, which is a situation where the model performs well on the training dataset but poorly on the testing dataset (IBM, 2024). Finally, the chosen model can be used to predict error probabilities for new projects based on their error-influencing attributes.

On the other hand, unsupervised learning techniques can uncover hidden patterns and structures. For example, clustering algorithms can group projects with similar error profiles together. This can reveal project characteristics frequently associated with errors, guiding feature/attribute selection for further refinement of the supervised learning models, where the initial error-influencing attributes conducted previously can be further reviewed and refined. Additionally, unsupervised learning can help identify data inconsistencies, improving the overall quality of data used to train the supervised learning model for error probability prediction in IHB assembly projects.

7.5.5 Tool Refinement

After testing and establishing the AI tool to predict future project errors in the assembly stage in IHB projects, the next step is to refine the tool further after each project. This is where CI practices like the Juran trilogy can be utilized by continuously learning from the experiences, planning for new improvements, and controlling the proposed improvements of this framework. As for the actual AI prediction model, the data collection is further updated by adding the new project's actual data to refine the model further and ensure more accurate predictions over time.

8 Discussion

After analyzing the collected data in light of the research questions, some reflections about implications emerged, mainly concerning the proposed tool's aftereffects. This chapter will discuss some of those implications, by exploring several implementations and discussing some of the challenges.

8.1 The Interaction of the Proposed Tool with IHB Managerial Practices

The first question that comes to mind about the proposed tool is, how can it be utilized in IHB construction companies? The proposed tool was mainly proposed to help in the planning phase, assisting project managers in the decision-making process when allocating the project's resources. This assistance is provided to the managers when they input the features/characteristics of the new project into the tool. By inputting this data, the tool can predict the probability of error occurrence in the project. However, the question is how does the tool predict? Or rather, what does it base the prediction on? The tool should be able to find similarities between the project's attributes from the historical records (in this study, which mainly consists of error records) and compare them with the current new project at hand. The output from the project will then show the errors that are most likely to appear in the project. A small example could be how the tool can predict that the errors increase when the numbers of subcontractors increase in the project.

Another example of the tool's effectiveness in assisting project managers' decision-making process is when allocating the most suitable subcontractor for specific project types. For instance, consider subcontractors A and B. Upon utilizing the tool, it emerged that subcontractor A has a lower number of errors than subcontractor B when working on a particular prototype. Conversely, subcontractor B had the fewest errors for other prototypes. Therefore, project managers can rely on the tool to make informed decisions, thereby enhancing the subcontractor selection process.

Providing the project managers with such predictions allows for a better decision-making process, especially when combined with the project managers' experience and knowledge. The prediction can prepare the team in advance to anticipate or mitigate the error. In fact, this is where the tool can be combined with other managerial practices, like planning for on-site construction activities. One example could be how the project manager could meet with the subcontractors to discuss how the anticipated errors can be avoided. Another example is, if the probability of an error happening is high, then the project manager can add additional time to the project timeline for error rectification.

The aforementioned information provides clear examples of how the planning process can help in reaching a more sustainable approach in the construction stage of IHB projects. This is because having such a tool can help by minimizing the overall timeline of the construction stage, minimizing the resource utilization by evading rework through better quality control measures, and finally providing the project leaders with valuable insight and time savings through the rapid analysis and automated data extraction process.

However, the utilization of the tool in managerial practices is not limited to the planning in the construction phase. For instance, prior to deciding on a prototype to develop, the designing team can utilize this tool by tweaking the new prototype's attributes to reach the most optimum prototype with the lowest error count possible. Another usage lies in risk management, where the project team can extract the error predictions to analyze the risks associated with them. If an error's effect on the project appears to be severe, then the project's team might decide to conduct an RCA to investigate the main cause of the error. Furthermore, the tool can help to investigate the errors that are persistent and repetitive in the project. Such errors can then be further analyzed with the help of PDCA to be able to develop a standardized solution that will ensure the mitigation of the error in future projects.

The proposed conceptual framework can also be divided into different parts, as each part could provide valuable implementations. One example is how the automated extraction process itself can help eliminate the manual administrative tasks that project leaders tend to spend a lot of time on. This alone can be the spark needed for construction companies to start working towards a more digitized approach by providing a step towards digitalization and the valuable benefit of time savings for the project leaders to spend on more valuable tasks.

8.2 Data Management in Light of the Proposed Tool

The proposed AI tool for error prediction in IHB projects illustrates the importance of robust data management practices. Several critical steps shall be considered to advance this tool from a conceptual framework to a practical application to ensure the effectiveness and efficiency of the proposed tool.

Firstly, the variations in inspection reports across different companies and among inspectors within the company were clearly noticed during the analysis. This variation poses a challenge for AI tools, as different data formats, levels of detail, and writing styles can affect the data preprocessing phase, thus affecting the learning process and prediction. To address such challenges, it is important to standardize the inspection documentation process by implementing standardized reporting formats, leading to a uniform and more efficient data collection process.

Secondly, it is clear that the data management strategies require significant enhancement. Many companies in the construction sector lack proper archiving methods, and a large amount of valuable project data remains unregistered or inadequately documented, especially when it comes to time-related data. To implement such AI tools in error prediction practices, it is important to establish robust data archiving frameworks that ensure complete data collection, secure storage, and easy retrieval. This could include developing frameworks or strategies for consistent data entry, regular updates, and continuous archival processes that support the long-term usability of the data.

8.3 Ethical Considerations

Several ethical considerations must be addressed regarding AI tools to ensure their reliability. First, data privacy and confidentiality must be secured, and all data must be protected per data protection rules, such as the GDPR, especially concerning personal-related data. This will guarantee obtaining clear consent from all participants about using their data, ensuring its safety, and preventing it from being accessed by unauthorized parties.

Secondly, the impact of such tools on employment shall be considered. The use of AI should be seen as a tool to enhance, not replace, the workforce. Specifically, the outputs of such tools can show how different employees are efficient in certain tasks while identifying areas of weaknesses. This information is valuable for optimizing resource allocation and identifying specific training needs, assisting the companies in preparing CI programs and professional development. This approach is far from displacing employees since the conceptual framework is designed to support the companies by providing insights that lead to more efficient management decisions and developing an environment where every worker can improve and succeed in certain strength areas.

Furthermore, while the proposed framework offers benefits in error prediction and management, it is crucial to maintain the professional judgment of experienced project managers. The proposed framework of the AI tool supports the experienced project managers' insights and decisions, not replacing their experience. This will ensure the balance between AI assistance and professional judgment by considering the insights provided by AI as supplementary to human expertise.

9 Conclusion

This study has explored the possibility of applying AI tools to predict errors in the on-site stage of IHB projects. It focused on enhancing the efficiency of the on-site phase through AI error prediction models. The research aimed to develop a conceptual framework that could assist project managers in better decision-making practices, improving overall project efficiency and quality, and better resource allocation.

Throughout the study, common on-site errors and their impacts have been investigated through a literature review, interviews, and analyzed inspection reports. Moreover, traditional error management and mitigation practices have been explored. The potential of AI in these areas has been thoroughly examined to provide a conceptual framework for AI error prediction tools. This framework is designed to capture AI capabilities in achieving error predictions and integrating them with project management practices, particularly in the realm of planning, thus supporting decision-making and resource allocation to enhance project efficiency and quality.

In this concluding chapter, the research questions provided at the beginning of the research will be answered, based on the results from the literature review, findings from interviews, and analysis of inspection reports. Furthermore, the study shows the need for further research in light of the proposed framework. Therefore, recommendations for future research will be provided, aiming to encourage continued exploration and refinement of the work initiated here.

How do IHB companies currently manage on-site stage errors, and what are the common causes and impacts of these errors?

In IHB construction companies, managing errors during the on-site stage contains a combination of strategies and methodologies. These methods include pre-job examination and risk management systems, which allow project managers to assess potential issues and better control errors. A common practice within these companies is project inspections. Besides mandatory inspections, many companies perform control and other inspections to reduce the number of errors effectively. Furthermore, quality KPIs and customer satisfaction measures are also used to identify weaknesses and errors, thus helping companies measure the project's overall quality and output. In addition, some companies offer best practice booklets to subcontractors and workers to mitigate and avoid errors in the assembly stage.

Moreover, some project managers employ personal efforts to address on-site errors. Experienced project managers often estimate the impact of errors based on past experiences or historical documents from similar projects, although the lack of standardized documentation formats can hinder this practice. Additionally, some project leaders evaluate subcontractors and workers, which could help ensure quality and affect future project selections. Another thought from the interviews is the early engagement of contractors, which can help mitigate errors, especially concerning communication and coordination-related errors.

Finally, methods such as PDCA, RCA, mistake-proofing, and Lean principles, which focus on waste and variation reduction, could contribute to error mitigation, even if some of these methods are not specifically oriented for addressing errors in the on-site stage. Such methods may offer solutions and help IHB companies to minimize errors and enhance project quality.

When it comes to common errors and causation, errors such as missing items, misalignment, inappropriate installation, and surface appearance were the most common error types mentioned in the findings, which were obtained from the literature and empirical data. The main cause of such errors was related to workmanship, communication, coordination, design issues, and other external factors. Such errors impact and affect the project's cost, time, rework, and customer satisfaction.

What AI models can be implemented to predict on-site stage errors in IHB projects?

Different ML models were explored in this research, assisting in the development stage of the conceptual framework of the AI prediction tool. One of the main tools was the NLP, which can analyze and interpret human language, making it applicable in the data preprocessing of the proposed framework. Furthermore, supervised and unsupervised ML models were explored to assess the applicability of these models in the proposed framework. For instance, supervised ML models such as Logistic regression and Linear regression are helpful in predicting errors, especially after having a structured dataset provided in the form of generic error codes and projects' error-influencing attributes. Such models can draw similarities and trends between the error probability and the error-influencing attributes. On the other hand, unsupervised ML models can be used to uncover hidden patterns and structures. For instance, clustering algorithms can group projects with similar error profiles together. These models can reveal the project attributes frequently associated with errors, which can help refine the previous supervised ML model and improve the overall quality of the prediction.

What are the potential benefits and challenges of integrating AI technologies into IHB companies?

The research explored several potential benefits and challenges of integrating AI technologies into IHB companies. One of the benefits is that AI can help project leaders estimate and predict various project aspects based on historical data, which can enhance the project's quality and save time. Moreover, AI tools can solve and automate data-related and administrative tasks, which are done manually, making them time-consuming. Another potentially helpful AI tool that can assist in data and documentation is the NLP, which can standardize data handling, increasing accuracy and consistency in project documentation. This can lead to better digitization processes. Furthermore, AI, particularly when using unsupervised ML models, could help in revealing hidden patterns that affect certain activities and provide significant insights that the project's team might not be aware of.

However, several challenges hinder AI implementation in IHB companies. Resistance to change is one of the major challenges, as some people fear that AI might replace their roles, and some people are skeptical about the usability of AI tools, as they might consider it complicated or inapplicable. Moreover, effective AI integration is limited by poor data management practices in the construction sector, where data is not properly registered, archived, or stored, making the implementation of AI tools difficult.

Main research question: ***How can Artificial Intelligence be applied to predict on-site stage errors in Industrialized House Building projects?***

The research question was addressed through the proposed framework provided in Figure (()). This framework outlines a structured process beginning with the data collection and ending with the refinement of the proposed tool. The conceptual framework delved into the preprocessing of data, the usage of NLP models for automating the preprocessing of data, and the usage of supervised and unsupervised machine learning models for the prediction process. This framework could be considered a practical roadmap for IHB companies aiming to integrate AI in on-site error prediction processes to mitigate errors effectively. Moreover, it bridges the gap between IHB companies and digital advancements, for smooth adoption of AI in IHB projects.

Finally, this research discussed integrating the proposed framework with managerial practices. The tool could provide significant insights for project managers, assisting them during decision-making, planning, and resource allocation processes.

9.1 Future Research

This study has explored AI's potential for predicting errors in the on-site construction phase of IHB projects. It has also provided a conceptual framework that could be considered a roadmap for AI's practical application in this field. Although this study has established a groundwork for using AI in error prediction, the proposed framework needs empirical testing with different ML models. This testing is necessary to refine the framework and evaluate the accuracy and effectiveness of the predictions. Therefore, future research could test this framework to determine the most appropriate ML models to be integrated effectively into IHB error management practices.

Moreover, further research could study the development of generic codes and attributes to enhance the AI tool's efficiency. Further studies could explore standardizing error classifications and expanding on the attributes to improve the AI model's learning and adaptability to different scenarios and project characteristics. This could help refine the proposed AI tool for better predicting and managing errors, thus mitigating them and their impact on IHB construction projects.

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Appendix

Appendix A:

Interview questions:

Background and Experience:

- Can you briefly describe your background and experience in construction project management?
- How many years have you been involved in industrialized construction projects, and in what capacities?
- What are the performance / productivity measures that you use (any KPI)?

Errors and Causes:

- From your experience, what are the most common errors that occur in the construction phase (assembly)?
- In your opinion, what are the primary causes of these errors?
- How do these errors typically impact project outcomes, such as time, cost, and quality?
- Which errors have the biggest effect on cost, time, and quality?
- And how often do they occur?
- Can you provide examples of significant errors and their consequences on past projects?
- What methods or processes are currently in place for detecting and preventing errors in projects?
- Are there any specific indicators or early warning signs that you look for to anticipate potential errors?
    - What types of data do you regularly monitor that could indicate the likelihood of an error?
    - How do you currently use data in planning and decision-making processes to mitigate risks?
- In your experience, how much do expertise and judgment play a role in preventing errors compared to data-driven methods?
- Are there aspects of error prediction that you believe are particularly amenable to machine learning?
- Based on your experience, what features or data points would you recommend be included in a machine learning model for error prediction?
- Are there any specific project phases or aspects where you think AI could be particularly beneficial in predicting errors?
- How do you envision the role of AI in future construction project management, particularly in error prediction and prevention?
- Are there any potential challenges or limitations you foresee in integrating AI into construction project management?

Previous questions from open interviews:

- Can you explain the processes of the installation stage (byggnation):
  - Is time registered?
  - For example, when materials arrive, time taken to complete a certain process.
  - Example: excavation time taken.
- When delays occur, what actions are done? Do you register or record something?
- Do you have a Dagbok? Do you register incidents there?
- Is there a timecard for the workers on site? Is it connected with the process?
- How is the synchronization between the factory and the on-site assembly?
- Is there a platform for this? Website to buy products?
- Is the data archived? With dates?
- Is the date of arrival of products registered?
- What is the performance / productivity measures that you use (any KPI)?
- How do you know the project succeeded?
- Do you use JIT delivery?
- Do you consider the Lean production system?
- Do you have any progress report?
  - Is it archived?
- How is the time (time plan) specified for different projects? (Table)
  - What factors decide the time.
- Do you have re-work in certain parts or elements? Is it registered?
- Which department sets the estimated plan?
- Give us a preview of how you work when you first begin a task of a construction project.
  - What are your responsibilities?
- Last Planner System (LPS), the Critical Path Method (CPM)
- Project management team responsibility? What about monitoring the process?

Appendix B:

Table 2. Total defect index list of cases.

Code	Occurring Time	Work	Location	Object	Phenomena
A1	occurring defect before handover	wooden structure work	ceiling	hanger	non-installation
A2				frame	unmatched size
A3				height	mismatch withdrawing
A4				molding	non-installation
A5		window and door work	door frame	finishing	excessive gap
A6					non-installation
A7			door	anti-rotting of end pieces	non-installation
A8				opening direction	overlap
A9			window and door		non-installation
A10			attachment		non-installation
A11			window and door		mismatch withdrawing
A12			others	caulking	non-installation
A13		finishing work	ceiling	molding	mismatch withdrawing
A14				finishing	mismatch withdrawing
A15			skirting board		mismatch withdrawing
A16			wooden floor	under kitchen system	non-installation
A17					non-installation
A18			interior furniture	attachment	non-installation
A19					mismatch withdrawing
A20					mismatch with industrial standard
A21					non-installation
A22		miscellaneous work	kitchen system	opening direction	overlap
A23				attachment	non-installation
A24	occurring defect after handover	wooden structure work	ceiling	structural part	malfunction
A25				molding	malfunction
A26					malfunction
A27		window and door work	window and door	finishing	opening and closing fault
A28					drop out
A29			door frame	finishing	malfunction
A30					flexure
A31					fault of attachment
A32					breakage
A33			door		malfunction
A34					flexure
A35				cover sheet	drop out
A36				bottom and end header	rotting
A37					drop out
A38			attachment	door lock	malfunction
A39				door hinge	malfunction
A40			others	caulking	malfunction

Table 2. *Cont.*

Code	Occurring Time	Work	Location	Object	Phenomena
A41		finishing work	floor	wooden floor	discoloration and breakage
A42			wall	wooden wall	malfunction
A43			skirting board	wooden skirting board	malfunction
A44			ceiling	wooden ceiling	malfunction
A45				wooden lighting box	malfunction
A46				wooden curtain box	malfunction
A47				well type wooden ceiling	malfunction
A48			others	caulking	malfunction
A49				cover sheet	drop out
A50			interior furniture		fault of attachment
A51					breakage
A52					opening and closing fault
A53				door hinge	malfunction
A54				molding	malfunction
A55				cover sheet	drop out
A56		miscellaneous work	kitchen system		malfunction
A57					breakage
A58					fault of attachment
A59				molding	malfunction
A60				door hinge	malfunction
A61				door	opening and closing fault
A62				cover sheet	drop out
A63			others	caulking	malfunction

Table 2. *Total defect index list of cases.* and Table 2. *Cont.* are both from the article by Park and Seo (2021).

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