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Challenges and Benefits of Implementing AI in Timber Construction for Circular Economy Goals

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Abstract: Artificial intelligence (AI) is considered an essential enabler of a circular economy (CE) in the construction industry. AI can significantly enhance the efficiency of applying innovative CE practices in other construction projects. However, it has not yet been fully integrated into the application of CE principles and has explicitly been overlooked in the context of timber construction. This study aims to bridge this gap by examining the potential contributions of AI applications to achieving CE in timber construction, as well as identifying the associated benefits and challenges. Through a mixed-methods approach, the research utilizes both qualitative data, collected through timber construction industry interviews, and quantitative analysis to explore professional construction perspectives and uncover actionable insights. The findings highlight the transformative potential of AI to enhance sustainability and operational efficiency in timber construction. Moreover, six potential benefits and 11 challenges for integrating AI and a CE in timber construction are identified that can act as an accelerator for advancing circularity in timber construction. Based on the results, the reduction in construction waste and facilitating the deconstruction and reuse process emerge as the most important benefits. Data obstacles, technological integration, finance and resources, and organizational and industry are determined as the main challenges. This study makes novel contributions to the field by providing empirical evidence in the form of qualitative and quantitative data, in addition to practical recommendations for advancing the integration of AI to promote CE goals and improve sustainability in the timber construction sector.

Keywords: architecture; circular economy; deconstruction and reuse; design; sustainability; timber construction

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1. Introduction

The transition of the built environment to a CE is essential to achieving the Sustainable Development Goals (SDGs) [1]. A CE refers to the prospect of reducing waste in construction and enhancing the resilience of buildings [2]. Under a CE, materials are used more efficiently, resources are conserved, and resources are not depleted [3]. A growing awareness of the importance of a sustainable environment has motivated Australia explore CE possibilities [4]. A central focus of the shift towards a CE is changes to the building sector and construction industry, which contributes to a significant amount of greenhouse gas emissions [5]. Globally, the sector is responsible for 36% of energy consumption and 39% of carbon dioxide (CO_2) emissions [6]. A total of 76 million tonnes of waste are produced annually by Australia's construction industry. Per million dollars added to the Australian economy by the construction industry, 87 tonnes of waste are generated, of which 27% is disposed of in landfills, and 16.8% is produced by the construction industry itself [7].

Evidently, construction needs to optimize resource use while reducing its environmental impact to achieve sustainability and encourage a shift towards a CE. This optimization requires changes to the ways construction materials are used, and the ways technologies are applied to construction projects. Among various construction materials, timber presents a promising option for achieving circularity due to its renewable nature and lower embodied carbon compared to concrete and steel [8]. Sustainable construction approaches can be further improved by using advanced digital technologies [9]. A rapid increase in technological capability in the construction industry in recent years has been made possible by the adoption of digitization [10]. Several new technologies have been adopted to enhance efficiency, productivity, accuracy, and safety, including AI, building information modelling (BIM), and digital twins (DT) [11,12]. Among these, AI stands out as a transformative technology capable of addressing key inefficiencies in timber construction, particularly in waste reduction, predictive analytics for material lifecycle optimization, and automated design for disassembly. AI enables the implementation of regenerative economic models in real-world practices and accelerates CE adoption [13]. Through AI, certain CE opportunities could be unlocked, including redesigning reusable products and optimizing resources. Designers can use AI to support the development of eco-friendly products by suggesting initial designs or adjusting them based on environmental parameters [14].

AI adoption in timber construction presents a number of benefits for the construction industry, including preventing cost overruns, improving site safety, increasing project planning efficiency, and enhancing site productivity [15]. Despite these advantages, AI adoption in timber construction for CE purposes remains limited due to challenges such as a lack of structured datasets [16] and non-standard building designs [17]. This study attempts to resolve these challenges by differentiating AI's potential role in timber construction for CE goals from its broader applications in general construction, addressing the specific challenges of reuse and deconstruction. Addressing these barriers will be key to enabling AI to effectively support CE objectives in timber construction. By identifying AI-driven solutions tailored to timber, this research provides a structured framework to enhance material circularity and contributes to deeper understandings of sustainable construction practices.

1.1. Background

The literature discussing AI in relation to construction predominantly focuses on AI's broad applications across architectural, engineering, and construction (AEC) sectors. For example, Momade et al. [18] conducted a review of the application of AI tools in AEC, categorizing the areas where AI has been applied, including structural engineering, construction materials, environment and transportation, hydrology, energy, project management, and geotechnical engineering. Within these applications, other studies have discussed AI's potential role in waste management and waste reduction. Alonso et al. [19], for example, developed and validated an AI model for the efficient self-management of waste, involving the automatic recycling of materials such as glass, plastic, paper, and organic materials through the use of image identification and convolutional neural networks.

Several studies have explored AI-driven approaches to enhance efficiency, accuracy, and sustainability in handling construction materials. Kroel et al. [20] developed a real-time monitoring system to analyze particle size distribution (PSD) in recycled aggregates using convolutional neural networks (CNNs) applied to 3D laser triangulation data. Their customized VGG-inspired CNN model achieved an accuracy of 80.8% for primary aggregates and 75% for recycled aggregates, demonstrating AI's potential in quality control and sustainability in construction material reuse. Similarly, Omer et al. [21] advanced the field by creating a 3D digital model to streamline pre-demolition audits and improve material recovery. Their method involved converting paper-based drawings into computer-aided design (CAD) models, automating 3D digital model generation, and integrating augmented reality for verification. This approach significantly reduced pre-demolition audit preparation from days to minutes, supporting systematic material reuse and minimizing waste contamination. Cabral et al. [22] investigated AI-assisted assessments of material reuse potential by integrating thermal imaging, RGB cameras, and depth sensors with machine learning (ML). Their system effectively evaluated material conditions, leading to optimized deconstruction processes, reduced material costs, and lower carbon emissions. The study provided actionable insights, particularly in the reuse of drywall, reinforcing AI's role in promoting sustainability in construction practices.

Beyond waste management, studies have also explored the integration of AI with other digital solutions, such as Internet of Things (IoT)-based sensors for monitoring and controlling aspects of construction projects. Rane et al. [23] employed AI-equipped smart sensors for the real-time monitoring of buildings' environmental conditions, energy consumption, and structural health. Similarly, Mehmood et al. [24] discussed the use of AI in designing and operating energy-efficient residential houses and commercial buildings, while Namlı et al. [25] and Farzaneh et al. [26] explored AI's potential to predict energy loads and optimize energy efficiency in buildings. Other studies have considered the use of AI for lifecycle assessment, life cycle cost estimation [27], and evaluating the energy and environmental performance of buildings [28].

Building on these broader applications, recent research examines AI's potential in CE practices within construction. Ulucan et al. [29] applied AI techniques to design sustainable concrete compositions by incorporating fly ash and recycled aggregates. Their approach utilized an interpretable AI-based rule extraction model to optimize compressive strength while minimizing the environmental impact. The study reported a 44.5% reduction in energy consumption and a 30% decrease in global warming potential, highlighting AI's effectiveness in optimizing sustainable material formulations for the construction industry.

AI has demonstrated potential in data-driven decision making, predicting product lifecycles, and optimizing CE strategies. Digital twins, for example, represent physical objects accurately and can be used to study performance over time [30]. By integrating IoT sensors, these systems can provide near-real time data on product condition and performance, which may ensure product longevity [31]. Based on these data, a product's performance can be optimized, extending its lifetime, and allow for intervening if necessary [32]. AI has also been shown to play a role in analyzing life cycle data to determine whether to reuse, remanufacture, or recycle a returned product [33].

Despite the abovementioned research on AI across several construction applications, research specifically focusing on AI's application to material reuse within CE in construction remains limited. Oluleye et al. [34], conducted a systematic literature review to identify 13 potential outcomes of implementing AI in circular building practices, including optimizing waste collection, improving site selection for construction and demolition waste recycling, reverse logistics in construction, and supporting sorting and segregation of building waste. Other applications include predicting aggregate strength for reuse, predemolition auditing for CE, and designing for waste prevention and disassembly. However, while these studies demonstrate AI's versatility in waste management and recycling, they primarily focus on broader CE practices rather than material reuse, which is central to CE.

AI has been explored in the context of timber construction, with a primary focus on design [35], structural performance [36], and fire resistance [37]. Man [35] has shown how AI can be used to automate the design and assembly of modular timber buildings. Bianconi and Filippucci [36] designed a timber structure using AI and CAD, demonstrating the potential for AI to optimize structural performance. Bianconi and Filippucci [36] used AI, specifically genetic algorithms, to optimize architectural forms in timber design. These algorithms were utilized within a generative design framework to analyze and understand the relationships among form, construction, and geometry, aiming to achieve optimized solutions that meet complex architectural requirements. Naser [37] suggested that AI could be used to assess the fire resistance and performance of timber structures, developing temperature-dependent material models for timber based on experimental data to enhance fire resistance evaluation. Naser [37] used AI in the form of a hybrid approach including artificial neural network (ANN), symbolic regressions, and genetic algorithms. Meanwhile, Olimat et al. [38] developed an ANN model to predict the effect of guided flames on timber species' combustibility. While these studies illustrate the potential of AI to enhance structural integrity and safety in timber construction, research exploring AI's potential contributions to facilitating CE strategies for timber construction remains undeveloped. The potential for AI to enable material reuse, disassembly, and material recovery in timber construction, key aspects of CE, is largely unexplored. While AI-driven waste classification systems focus primarily on end-of-life recycling, material reuse—particularly in the context of CE principles—remains a significant gap.

In addition to the limitations of research into AI for timber construction, AI research in construction has not adequately addressed the ethical and practical challenges associated with AI in construction more broadly. Floridi et al. [39] identified various risks related to the unethical use of AI, including algorithmic bias, economic inequality, and data privacy concerns. Roberts et al. [30] identified several plausible risks associated with the unethical use of AI including epistemological risks, economic inequality and exclusion, algorithmic bias, and data privacy. Focusing on practical challenges, Abioye et al. [10] identified the key challenges of AI application in construction processes, including shortages of trained staff, computing power and internet connectivity, security limitations, ethics and governance, high initial costs, cultural issues, and explainable AI. In the context of timber construction, overcoming these challenges is particularly crucial due to the lack of AI-integrated frameworks for evaluating reclaimed materials and optimizing reuse pathways. Addressing these barriers will be key to enabling AI to effectively support CE objectives in timber construction. This study seeks to overcome these challenges by focusing on AI's role in enhancing deconstruction planning, facilitating real-time material tracking, and integrating predictive analytics to maximize the reuse potential of timber.

Table 1 summarizes some potential function categories of AI from a practical perspective in construction, with a focus on a CE. Each category is explained based on the literature. The table provides a theoretical framework to support the investigation, and these functions will be examined in the context of timber construction in the following sections.

Table 1. Summary of proposed AI function categories in relation to CE in various contexts.

AI Function Categories	Examples in Various Contexts
Design optimization	AI is used in engineering and construction to optimize design solutions by analyzing multiple constraints and objectives. ML and deep learning techniques assist in generative design, enabling architects and engineers to create high-performing and resource-efficient structures [10]. In architectural applications, AI enhances material selection and composite development, optimizing for criteria such as structural durability and energy efficiency [11].

Table 1. *Cont.*

AI Function Categories	Examples in Various Contexts
Environmental impact assessment	Deep learning algorithms help assess the life cycle costs of buildings, supporting data-driven sustainability decisions [27]. AI-driven models, including ML and big data analytics, are applied to predict the environmental impact of buildings across their life cycle [28]. In architectural engineering, AI assists in real-time carbon footprint estimation and optimization of low-carbon designs [40].
AI-driven building and material performance	AI enables real-time monitoring of structural health, energy consumption, and environmental conditions in the built environment [23]. In material selection, AI predicts the strength and reuse potential of construction materials based on CE principles [34]. Additionally, deep learning models enhance defect detection in buildings by identifying deterioration patterns such as mold growth, paint deterioration, and structural weaknesses from image-based analyses [41].
Modeling, simulation, and decision support	AI-powered decision-support systems improve the efficiency and feasibility of complex modeling tasks in the AEC. ML algorithms enable predictive simulations for structural analysis, risk assessment, and construction planning. These AI-driven models provide enhanced accuracy and speed in evaluating construction scenarios, supporting data-driven decision-making processes [18].
Energy efficiency and prediction	AI-based predictive models analyze building energy consumption patterns to optimize efficiency [25]. In residential and commercial buildings, AI is used for energy load estimation, demand forecasting, and automated control of smart building systems. ML and deep learning techniques improve energy management strategies by predicting future consumption and enabling real-time adjustments to minimize waste [26].

1.2. Aims and Objectives

While AI has been recognized in the CE literature for its transformative potential in construction, its specific role in integrating AI and a CE remains underexplored [42]. In particular, research on AI's potential to facilitate circularity in timber construction is limited. A review of the existing literature reveals only a few studies discussing the benefits of AI applications in the timber construction industry for CE purposes. Although AI has been applied in some CE-related research, the challenges of integrating AI into timber construction to enhance circularity remain insufficiently addressed.

This study aims to bridge these gaps by systematically investigating AI-driven approaches tailored to timber construction. The study objectives are as follows:

1. Analyze the potential contributions of AI applications in advancing a CE within timber construction;
2. Identify potential benefits of integrating AI and a CE in timber construction;
3. Uncover potential challenges to implementing AI in timber construction to promote CE purposes.

2. Materials and Methods

In order to address the research objectives, a mixed-method approach, including interviews and an online survey, was used. Through this approach, both quantitative and qualitative data were collected. Interviews to gather qualitative information and gain a deeper understanding of participants' perspectives precede an online survey (quantitative data). The research flowchart of this study is presented in Figure 1. First, the identified examples of AI functions in different contexts from the literature were used for the interview process. Second, semi-structured interviews were conducted to address research objectives.

Finally, an online survey was used to obtain quantitative data. In the following section, each interview and survey method are discussed separately. The protocol for the study was reviewed and approved by the host university research ethics committee (HC220658).

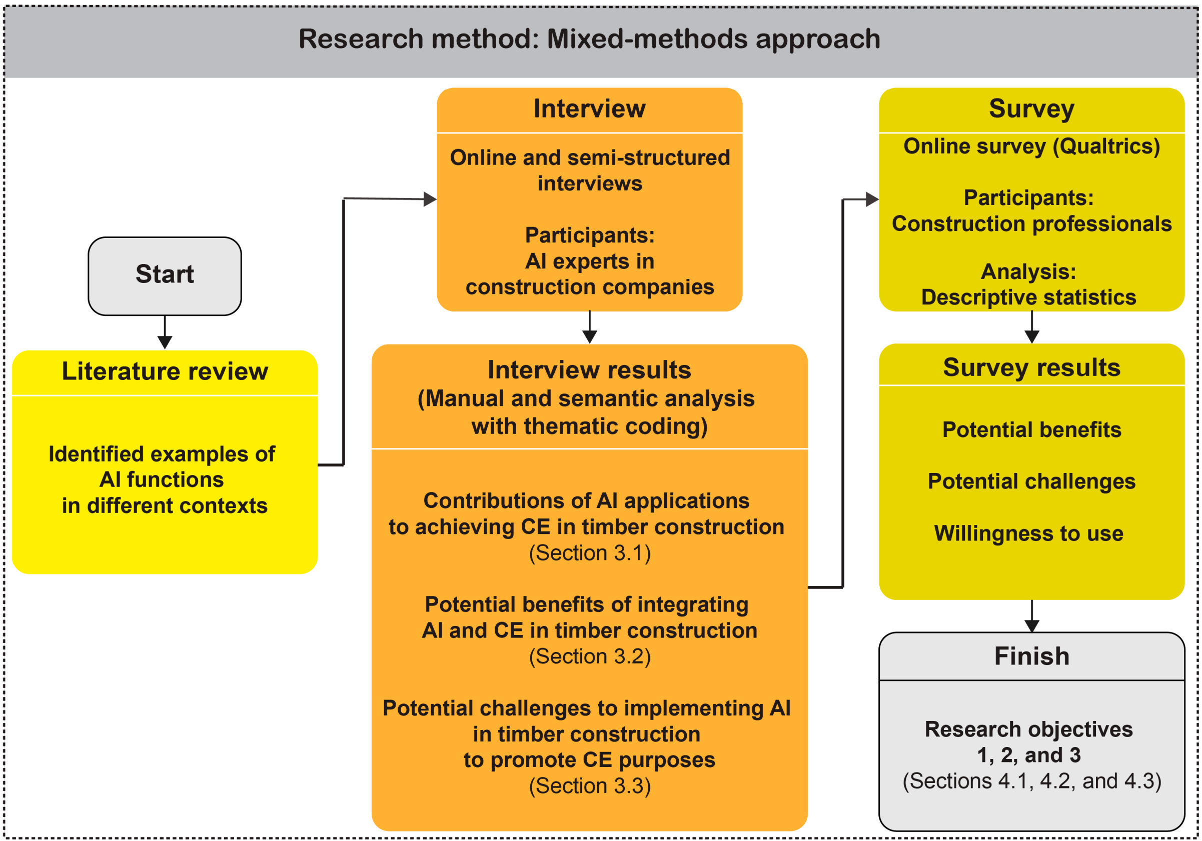


Figure 1. Research flowchart including details of the mixed method employed for this study.

2.1. Interview

Participants were recruited via an online platform as a part of the semi-structured interview approach. Ten AI experts in Australian construction companies were interviewed. Interview sessions were conducted to gain insight into the perspectives and experiences of AI experts. The recruitment of participants was based on a chain strategy [43]. This strategy helped identify experts in the field with the relevant experience to answer questions, enhance the richness of data, and make data more valuable and unique by choosing appropriate participants. Due to the presence of semi-structured questions in the interview questions, participants were selected using a purposive sampling method. Using semi-structured questions, researchers can gather different types of information [44]. The selection of participants who had information about AI and CE was determined by a purposeful sampling method. Qualitative and narrative responses are collected from participants using a non-probabilistic approach [45].

Notes were taken, and the interview was recorded to ensure data reliability and minimize bias. Table 2 shows anonymous information about interviewees based on their answers to background questions. Each participant was given a unique identification code to ensure anonymity and confidentiality. Interview questions were designed to determine the integration of AI in timber construction with a focus on CE and uncover potential challenges to implementing AI in timber construction. Moreover, detailed questions concerning the benefits of using AI in the design stage of timber construction projects were asked. Primary and qualitative data from semi-structured questions were used for analysis. Manual and semantic data analysis were used with thematic coding to interpret the interview transcripts. All data were categorized using a thematic analysis approach [46].

Table 2. Interviewee background information.

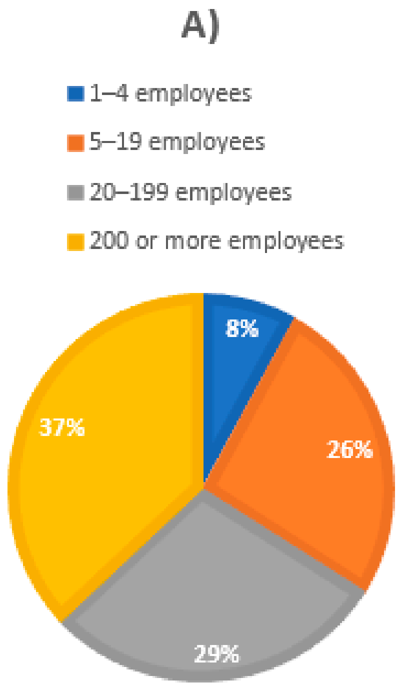
No.	Current Role	Years of Experience	Areas of Expertise	Company Size
1	Project manager	20	AI expert familiar with CE	200 or more employees
2	General manager	20	AI expert somewhat familiar with CE	5–19 employees
3	Computational designer	10	AI expert somewhat familiar with CE	200 or more employees
4	Principal machine learning engineer	>16	AI expert familiar with CE	200 or more employees
5	Senior software engineer	>20	AI expert familiar with CE	1–4 employees
6	Digital innovation leader	10	AI expert somewhat familiar with CE	200 or more employees
7	CEO	25	AI expert familiar with CE	1–4 employees
8	Associate urban designer	6	AI expert familiar with CE	20–199 employees
9	Engineering director	18	AI expert familiar with CE	200 or more employees
10	Co-founder and CEO	7	AI expert familiar with CE	5–19 employees

2.2. Survey

An online survey was designed for the potential participants after the interview process. Qualtrics platform was a secure online platform for potential participants to complete the survey. The survey was conducted to gather a larger sample size for a broader perspective on the research objectives. To recruit the participants, the same strategies (criterion-based and chain strategies) as mentioned in the interview section were applied. LinkedIn was used to identify participants, and websites of relevant construction companies in Australia were searched to identify those interested in participating in the survey. In this study, 102 professionals from a range of Australian construction companies were selected by snowball sampling. Figure 2 shows demographic information about survey participants. Most of the participants were familiar with the CE model, and they had more than 10 years of experience in the industry and worked in medium to large companies.

Several types of questions were included in the survey, including closed-ended questions and multiple-choice answers. The survey had four main sections, including demographic information, expertise assessment, core questions, and future directions. For instance, the core questions were about the participants' opinions about the contribution of AI to achieving CE in construction, the potential benefits of using AI for CE purposes, and the potential challenges for implementing AI to promote CE purposes. The survey method was analyzed using primary and quantitative data. Through the survey platform, participants were assured of the security and anonymity of their data. Descriptive statistics were used to analyze the questionnaire results. The SPSS program (percentages and frequencies) analyzed the survey results.

Key role	No.
Project manager	25
Civil engineer	19
Architect	13
Technology officer/AI engineer	8
Site engineer	7
Contract manager	6
Technical manager	6
Structural engineer	5
Consultant in CE	3
Building service engineer	2
Construction manager	2
Estimator	2
Director	2
Joiner	2
Total	**102**



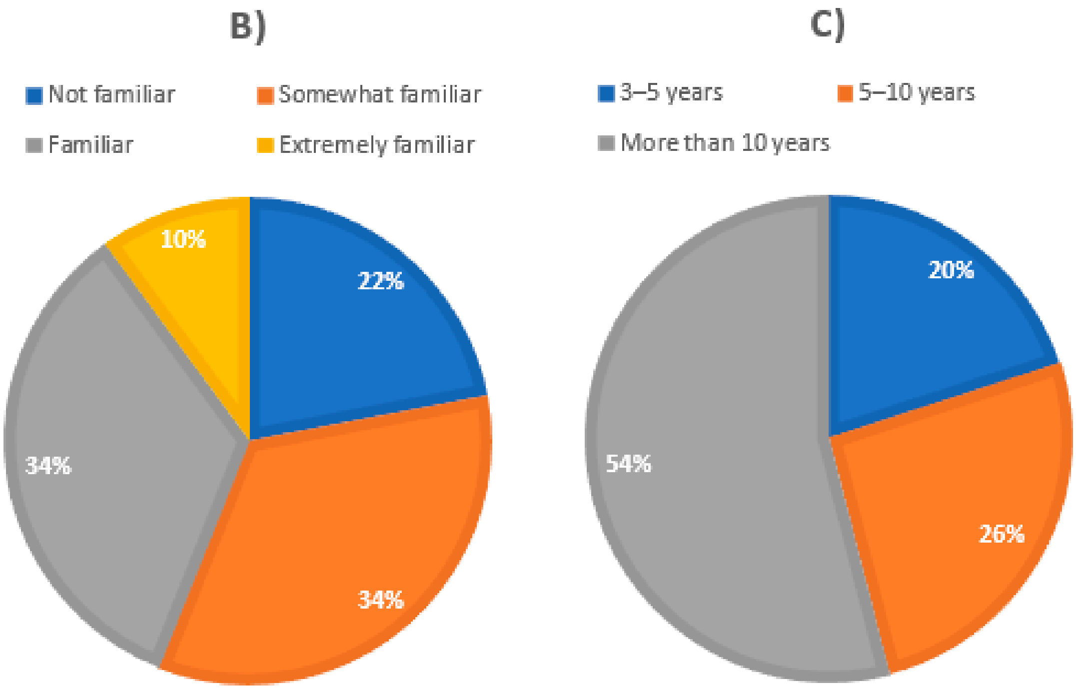


Figure 2. Survey participants' background information: (**A**) company size, (**B**) familiarity with the CE, and (**C**) years of experience.

3. Results

This section presents the results in three sub-sections, including the contributions of AI to achieving a CE in timber construction (Section 3.1), potential benefits of integrating AI and a CE in timber construction (Section 3.2), and potential challenges to implementing AI in timber construction to promote CE purposes (Section 3.3). Each sub-section addresses one of the research objectives by analyzing the interview quotations, followed by the survey results. The statistical significance (p-value) test results revealed differences in response patterns across the survey questions.

3.1. Contributions of AI Applications to Achieving CE in Timber Construction

Based on the interview findings, CE purposes, especially in the timber construction industry, are achieved with AI algorithms and applications. In order to develop an AI algorithm (based on Interviewees 7 and 10's explanations), data are collected, data engineering is applied, the algorithm is developed, and the algorithm is refined to solve a particular challenge. Firstly, images and other metadata are captured to collect the required data. Following consistent data labeling, an algorithm is developed, and the data are engineered into a machine-readable format. Through iterative processing, the algorithm learns from training data sets until it can generalize its learning to new and unknown data, which enables its use in real-life applications such as visual recognition.

Various AI applications in timber construction are presented in Table 3 based on the interview findings and the AI functions identified in the literature. To demonstrate how AI can be applied to timber construction projects, each application, including predictive analytics, ML, computer vision, and blockchain, is accompanied by related AI functions to achieve CE purposes. Based on Interviewee 2's explanations, the blockchain-based system for tracking construction materials throughout their lifecycles provides a transparent and immutable record-keeping system. Using this system to track metrics becomes essential due to its unique ability to provide secure and transparent records to minimize construction waste. By utilizing smart contracts, which are self-executing agreements with terms written directly into code, waste management in timber construction will be automated, and environmental sustainability standards will be maintained. Based on an interviewee's opinions (Interviewee 9), the integration of blockchain and DT leads to smarter and lower-energy manufacturing systems and materials by tracking and verifying carbon footprint and energy consumption.

The cameras and sensors equipped with computer vision play an important role in improving construction quality and efficiency, based on explanations from Interviewees 4 and 7. This happens especially when it comes to tasks requiring high-accuracy visual assessment, like identifying defects and components' features (refer to Interviewee 4). This system identifies recyclable and reusable materials, detects material defects, and monitors the performance of buildings in real-time, to facilitate the deconstruction process (refer to three interviewees). Several techniques have been developed to detect defects and identify reusable materials, including pattern recognition (Interviewee 7), object detection (Interviewee 7), and image segmentation (Interviewee 6). As a result of this process (mentioned by three interviewees), the reuse of high-quality materials is ensured, which increases resource efficiency and reduces waste.

Moreover, in timber construction, the ML plays an essential role in enabling sustainable practices due to its broad applicability (based on eight interviewees' explanations). By developing ML algorithms, timber construction and circularity are enhanced in various ways by developing optimization algorithms and predictive models (refer to Interviewee 7). This algorithm is a key component of different identified AI functions. For instance, with the help of ML algorithms, analyzing a tremendous amount of data from past projects is possible for structural engineering (refer to Interviewee 2). Identifying efficient design and material options is conducted to reduce construction costs and resource consumption (refer to Interviewees 3 and 7). Predicting timber structural performance under various conditions is conducted by creating models that utilize techniques such as decision trees, neural networks, and regression analysis (refer to Interviewee 2). Forecasting future trends and predicting maintenance needs are possible because of predictive analytics to minimize resource usage and reduce environmental impacts (refer to Interviewee 2). This application combines historical data with forecasting to predict future trends and outcomes (refer to Interviewee 6). The predictive maintenance model uses information from past maintenance records and sensors to determine the time and the location of the maintenance needs (based on four interviewees' explanations). This prevents unexpected and costly breakdowns (refer to Interviewee 2). Potential issues can be identified using techniques such as time-series analysis (refer to Interviewee 5).

Table 3. AI applications with their related AI functions for CE purposes in timber construction.

AI Application/AI Function	Blockchain	Computer Vision	ML	Predictive Analytics
Optimizing building designs			☑	☑
Suggesting energy-efficient design			☑	☑
Generating building design			☑	☑
Optimizing building cost			☑	☑
Simplifying/improving modeling processes			☑	
Conducting material selection for building construction		☑	☑	☑
Minimizing waste	☑		☑	
Detecting material defects		☑	☑	☑
Real-time monitoring of building performance and conditions		☑	☑	☑
Estimating energy rating of buildings			☑	☑
Analyzing building energy efficiency			☑	☑
Predicting maintenance needs			☑	☑
Recording real-time building and elemental performance		☑	☑	☑
Predicting lifecycle assessments of buildings			☑	☑
Analyzing environmental impacts			☑	☑

3.2. Potential Benefits of Integrating AI and CE in Timber Construction

Based on the interviewees' responses, there are some benefits to the integration of AI into timber construction for CE purposes. The key benefits of integrating AI into timber construction for CE purposes include the reduction in construction waste, lower energy consumption, improved building lifespan, enhanced project planning and scheduling, the circularity of the products/materials, and the creation of new business models. In the following, the interviewees' quotes about these benefits are expressed to provide more details.

One interviewee (Interviewee 9) discussed the reduction of construction waste benefit by mentioning *"applying AI within a business to optimize a flow in a way that reduces the overall waste of the system"*. He also discussed the enhanced project planning and scheduling benefit by providing the example of *"a lot of plans and schedules [tasks], especially for logistics and supply chain considerations can be conducted"*.

Another interviewee discussed in detail the improved building lifespan benefit by providing the following example:

"ML models that given enough data, you can begin to predict the behavior, and that would enable you to predict the maintenance requirements [...] to increase the buildings' lifespan". (Int #2)

Two interviewees discussed in detail the circularity of the timber products and materials benefit by providing the following examples:

"In the future, when more of our buildings are prefabricated, like mass timber construction, you might be able to unbolt the beams and reuse the beams. AI will be able to assist with that, if you've got a big enough data set, and you know where all of the prefabricated beams are in all of the buildings across an entire city. And you can say, well, five buildings are coming towards the end of life that 35 years old, they're not tenanted, maybe, instead of demolishing them, we'll deconstruct those, and then over here, we can reuse them in a new building". (Int #2)

"AI could be applied to figuring out new ways with low energy to deconstruction or return them into the base components that could be then reused into something else". (Int #9)

Moreover, one interviewee discussed in detail the lower energy consumption benefit by providing the following example:

"I think it is just a matter of time until you have full AI designed buildings. And I'm sure this would probably be more effective from an energy point of view".(Int #3)

Lastly, one interviewee discussed in detail the benefit of creating new business models by providing the following example:

"Using large language models and open AI to help businesses for optimizing business work. [...] the main focus is about using AI or ML in a design process of like one product". (Int #5)

The benefits outlined above illustrate AI's potential to drive sustainable CE practices. Some of the above-mentioned benefits require further explanation due to the significant advantages of using AI in timber construction. Optimizing building designs, suggesting energy-efficient designs, optimizing structural engineering calculation, optimizing building cost, optimizing resource usage, facilitating the deconstruction process, and detecting material defects are the benefits discussed further in the following paragraphs.

Incorporating AI into timber construction at the design stage provides the advantages of accuracy, productivity, flexibility, and modeling capability. One interviewee highlighted the advantages of using AI in optimizing building design by providing the following example:

"Over many years, you are doing hundreds of thousands of runs on several supercomputers. But to run a new timber slab on the ground model in the software that allows designers to significantly optimize the design, it would take two days to run an individual dwelling calculation. We've used ML techniques to take those hundreds of thousands of runs, and we used the heat three model that we can then insert into [a] software, which will run in a split second and deliver 99.9% accurate results. So, we hope to streamline a whole range of really demanding computational routines and, thus, improve our modeling capabilities". (Int #1)

Based on the findings above, AI facilitates the optimization of design by evaluating various design variables, including cost, to identify the most efficient design solutions. Moreover, AI enables the adaptation and modification of timber building designs to address evolving requirements, highlighting its significant advantage in terms of flexibility. Another interviewee highlighted the advantages of using AI in suggesting energy-efficient designs for timber buildings by providing the following example:

> *"There's a company called Giraffe, trying to build in design options for building efficiency. So, they'll give you an option, and they'll give you an analysis, solid game, or shading".* (Int #2)

As a result, AI-driven design processes enhance the energy efficiency of timber buildings, contributing to the CE.

Another advantage of using AI in timber construction is related to its capability to make timber structural engineering calculations more efficient (refer to Interviewee 2). This efficiency refers to the speed and accuracy of the calculations. In this regard, one of the interviewees mentioned the following:

> *"Who does structural engineering calculations? You would be running the same calculations over and over, and that is very inefficient. But my point here is that they would have a very large library of calculations, which get run quite regularly and, like that, lends itself to a ML approach. I'm sure that they could make the calculation process much more efficient through that".* (Int #2)

Interviewees expressed cost optimization and reused capability as the advantages of using AI by providing two examples:

> *"If you're a big development company that has a lot of assets as probably a lot of land, and you have a series of projects to use as models, then potentially you could use AI to look at what the available materials are and try to run generative models to see how much the cost of potential developments could be impacted by using the available materials to reuse. The thing with AI is it's not very easy to plan so much ahead. Like when you have the task in hand, and you see its benefits and its potential".* (Int #3)

> *"If it's all about materials and reusing materials, I would say there would be potential to optimize how different materials are used on a project. For example, whether it be timber, minimizing those materials so you could deploy algorithms to kind of analyze and test how to do that".* (Int #6)

A further advantage of using AI in timber construction is related to its ability to enhance the future deconstruction or demolition capabilities of timber buildings. Timber buildings can be demolished for recycling purposes, while they can be deconstructed for reuse purposes. One interviewee gave an example related to the demolition process:

> *"Using drones and image capture software and then just using AI to analyze the imagery to understand the quality of material usefulness, to help with the kind of demolition process like the staging of demolition to understand which parts we need to break down further to better utilize those materials".* (Int #8)

Another advantage of using AI in timber construction is its potential for efficient deconstruction, which assesses the quality of timber materials and components and detects defects. Through this efficiency in the deconstruction process, timber materials are recovered and evaluated for reuse in other construction projects (refer to Interviewee 9). In this regard, one interviewee mentioned the following example:

> *"The inspection [of a timber] could be done through cameras through some sensors through some devices that could measure, maybe not on a brick spoke timber, you can look to log, maybe each log, maybe you need to sample some logs statistically, and then you can evaluate those or the evaluate endurance with specific devices that meant to measure the difference, you can have a visual inspection of this, again, sample blog. And then you can have a visual inspection of those. And absolutely, an AI model can help you with those evaluations with endurance and quality assessments that are not visual".* (Int #4)

The survey data confirmed these interview findings, which highlighted AI's potential to reduce timber construction waste and expressed its positive impact on lower energy consumption. Furthermore, the survey respondents highlighted the impact of AI on enhancing project planning and scheduling. The survey responses identified these three benefits as the most important ones for integrating AI for CE purposes. The identified benefits are categorized into three different categories: environmental and resource efficiency, operational and project efficiency, and economic and business innovation. The environmental and resource efficiency category includes the reduction in construction waste, lower energy consumption, and providing the circularity of the products or materials. Operational and project efficiency includes enhanced project planning, scheduling, and improved building lifespan. Lastly, economic and business innovation includes the creation of new business models. The full list of potential benefits of integrating AI and CE, their categorization, and their survey response percentages are illustrated in the following Figure 3. Moreover, based on the survey responses, one of the key potential benefits of integrating AI and a CE was related to its effect in providing the circularity of timber products or materials. The circularity of the timber products or materials is conducted via their reuse and recycling. As part of Figure 3, the percentages related to different ways that AI contributes to reusing and recycling timber materials and elements based on survey responses are illustrated.

Based on Figure 3, using AI enables more efficient waste management, significantly reducing timber construction waste. Efficient waste management is conducted by sorting construction waste at the end of the timber building's life (refer to Interviewee 9). This is supported by another study conducted by Sharma et al. [47]. Moreover, AI ensures that timber buildings are designed to be energy efficient, thus reducing their energy consumption and enhancing their durability (refer to Interviewee 3). Additionally, AI improves project planning and scheduling, reducing the likelihood of costly delays and resource waste, maximizing resource utilization, and staying on schedule (refer to Interviewee 9). By facilitating the deconstruction and reuse of timber building components, AI contributes to circularity (refer to Interviewees 2 and 9). It also promotes the repurposing and recycling of timber products and materials (refer to Interviewee 2). Finally, AI-driven business models provide insights that can be leveraged to enhance profitability and sustainability within the timber construction industry, creating new opportunities for innovation (refer to Interviewee 5). As a result, based on the survey respondents, AI enables more sustainable construction practices and drives CE initiatives in the above-identified categories. The environmental and resource efficiency category was chosen as the first selected category, followed by the operational and project efficiency and economic and business innovation categories, respectively. This category is chosen because it aligns with the global trend of emphasizing the SDGs and immediate environmental impact on the construction industry.

In the case of how AI contributes to reusing and recycling timber materials and elements, the survey respondents (refer to Figure 3) highlighted the impact of AI on analyzing data on existing building materials and recommending suitable reusing options, respectively. Moreover, identifying salvageable materials and components, facilitating the deconstruction process, and efficiently sorting reusable elements were the other impacts of AI on reusing and recycling materials and elements to promote CE.

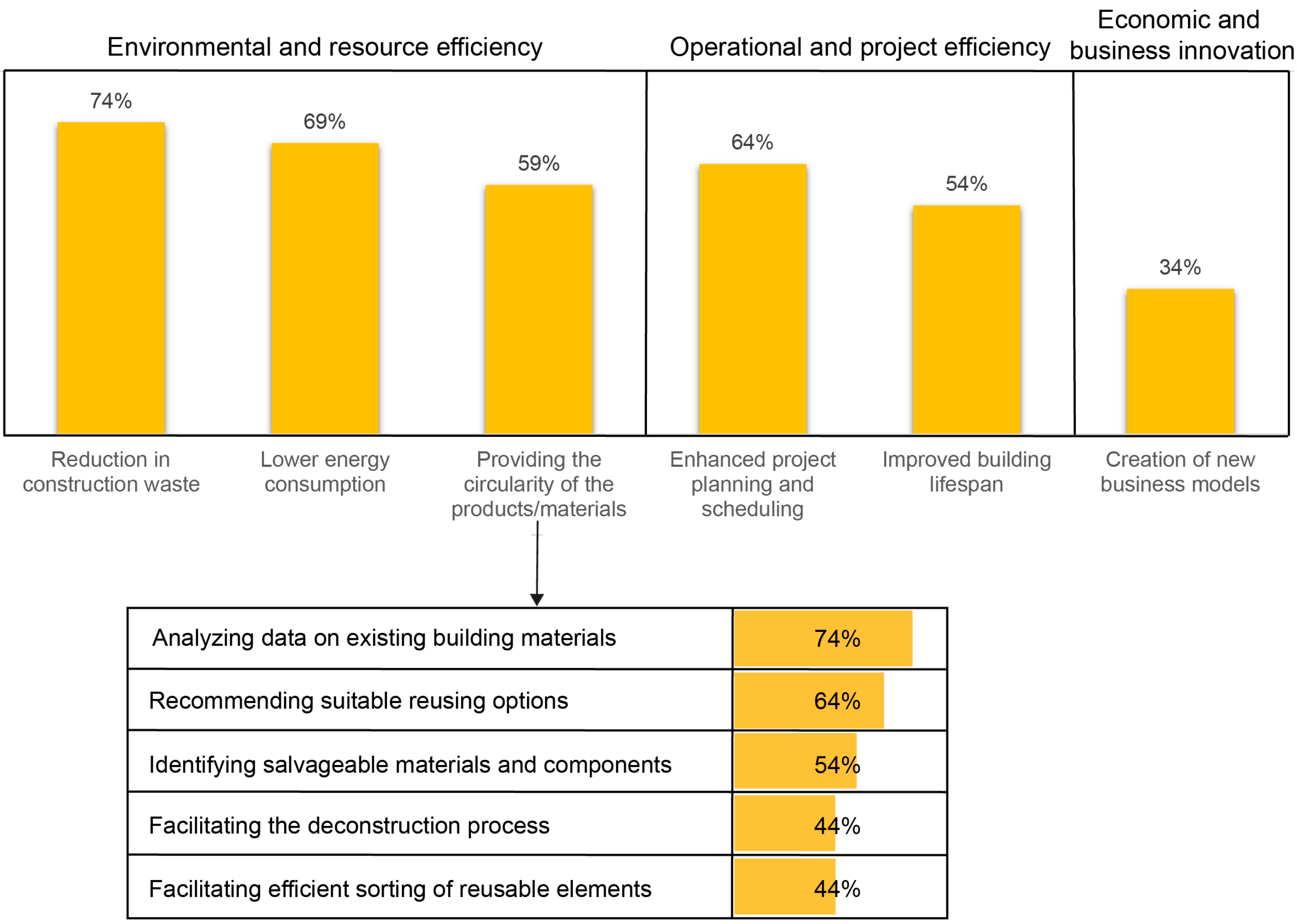


Figure 3. Potential benefits of integrating AI and CE in timber construction and AI contribution to reusing and recycling timber materials and elements based on survey responses.

3.3. Potential Challenges to Implementing AI in Timber Construction to Promote CE Purposes

Despite the benefits, implementing AI for CE purposes in timber construction faces several challenges.

Table 4 presents the relevant interviewees' quotes related to eight challenge codes that emerged from the transcription analysis. The interviewees' quotes support each code and refer to a specific challenge related to the implementation of AI for CE purposes in timber construction. Challenges cover the lack of availability of high-quality data from the building's lifecycle, data fragmentation due to various stakeholders, data privacy and security concerns among stakeholders, and the challenges of connecting AI to 3D models. Additional challenges involve the lack of AI models specific to different construction materials and their circularity, the need for high initial investment in AI infrastructure, the resistance to technological change within the industry, and the lack of skilled personnel for AI integration. The explanations related to each challenge are provided in the following paragraph.

Table 4. Challenges of implementing AI in timber construction to promote CE based on interviewees' quotes.

Challenges (Transcription Codes)	Selected Quotes
Lack of availability of high-quality data from the building's lifecycle (from extraction to demolition)	*"There are no large datasets to draw on to help with the design process, so a lot of architecture and engineering practices are now going through the process of standardizing and storing data".* (Int #6) *"More collaboration between firms and the standardization of design data essentially is the issue".* (Int #6) *"The data is available, but the consistency and quality of the data are questionable".* (Int #8)
Data fragmentation due to various stakeholders	*"The technology has limitations if you don't have the right data, you need then the application of that data is not possible".* (Int #9) *"To gather all information and data, it is not trivial to find the relevant experts, labs, and equipment".* (Int #4) *"Quality data exists but it needs to be usable, consistent, available, and in the usable format".* (Int #7) *"There is a need to collect big enough dataset, [. . .] need for an interconnected dataset that pulling from a different dataset".* (Int #2) *"The challenge and why it's a manual task is because this information was scattered across a lot of different systems, and it might be unstructured data".* (Int #9)
Data privacy and security concerns among stakeholders	*"Sometimes it's hard to get data as an outsider. Construction companies have their own data, but they also hate sharing it".* (Int #10)
Challenges of connecting AI to 3D models	*"There is a challenge of connecting AI to 3D models".* (Int #3) *"We're using stable diffusion and Midjourney to generate images. You can't control the structural layout of an image".* (Int #8)
Lack of AI models specific to different construction materials and their circularity	*"[. . .] technical challenge of building the relevant model".* (Int #4)
Requiring high initial investment in AI infrastructure by companies	*"[. . .] not economically feasible".* (Int #2) *"These projects cost huge amounts of money".* (Int #7) *"It's not always in our best interest to start pursuing new technologies or innovative ways of doing things because we just don't have the time or the money to do that".* (Int #8)
Resistance to technological change within the industry	*"There is not a clear stakeholder who owns the information, [. . .] architects do not care about stakeholder downstream".* (Int #2) *"Construction is such an old-fashioned or traditional industry, very resistant to change".* (Int #7) *"Change management is a big challenge if there are entrenched processes. Getting people to change the way they do things is difficult".* (Int #9) *"Construction industry moved very slowly. It's very conservative".* (Int #10)
Lack of skilled personnel for AI integration	*"There is a need for skills and expertise in this area".* (Int #7) *"We don't have many people that know about both AI and construction".* (Int #10)

Three interviewees highlighted that providing high-quality data from the timber building's lifecycle is one of the most significant challenges facing AI in the timber construction industry to promote a CE. One interviewee (Interviewee 6) pointed out that large and standardized datasets from timber buildings are in short supply for effective AI integration. In detail, the interviewee mentioned that *"there are no large datasets to help with the design process"*. *"The data is available, but the consistency and quality of data are questionable"*, as stated by another interviewee (Interviewee 8). As a result, data collection and storage practices must be standardized industry-wide (refer to Interviewee 6). Moreover, four interviewees pointed out that AI is limited in its ability to analyze and predict because of the inconsistency of the available data. Various stakeholders involved in the process contribute to the fragmentation of data (refer to Interviewee 2). Data collection and integration are complex tasks, according to five interviewee responses. This fragmentation of data makes it difficult to create a cohesive and usable dataset because the data are scattered across different systems in unstructured formats (refer to Interviewee 9). The complexity of data sharing and collaboration is further complicated by concerns over privacy and security, as mentioned by Interviewee 10. Three interviewees have commented on the difficulty of sharing proprietary information among construction companies. AI models for different construction materials and their circularity are also lacking, and it is difficult to connect them to 3D models (refer to Interviewees 3 and 8). In addition, three interviewees highlighted that AI infrastructure requires a high initial investment, which is prevented by construction companies. Furthermore, in the traditional conservative construction industry, there is resistance to technological change, which further impedes the adoption of AI (refer to four interviewees' opinions). Because of its old-fashioned nature, the construction industry is very resistant to change, which has been extended to timber construction (refer to Interviewee 7). These challenges are further compounded by a lack of AI experts in timber construction (refer to two interviewees' opinions). To leverage the potential of AI for CE growth in timber construction, these multifaceted challenges must be addressed.

In order to obtain additional information regarding the challenges of implementing AI in timber construction, the above-mentioned challenges were used in the survey. Similarly, survey respondents pointed out the same key challenges identified in the interview, while some highlighted other challenges. The different challenges identified in the survey responses were 'not being integrated by BIM and geographic information system (GIS)' and 'working against current building practices and businesses'. These challenges are more related to the entire construction industry, not specifically to timber construction. In Figure 4, the above-identified challenges (including interview and survey analysis) are categorized into four categories. These categories include data challenges, technological integration, financial and resource, and organizational and industry challenges. Data challenges cover the lack of availability of high-quality data from the building's lifecycle, data fragmentation due to various stakeholders, and data privacy and security concerns among stakeholders. The technological integration challenges category covers the challenges of connecting AI to 3D models and not being integrated by BIM and the GIS. The financial and resource challenges category covers requiring a high initial investment in AI infrastructure by companies and a lack of skilled personnel for AI integration. Lastly, the organizational and industry challenges category covers the lack of AI models specific to different construction materials and their circularity, the resistance to technological change within the industry, and working against current building practices and businesses. The following Figure 4 indicates the percentages of each challenge selected by the survey respondents.

Based on the findings above, the lack of high-quality data from the building's lifecycle was the biggest challenge chosen by the survey respondents. Akanbi et al. [48] highlighted this challenge by expressing the lack of available real-life datasets for the circularity of construction wastes. Moreover, requiring a high initial investment in AI infrastructure by companies, resistance to technological change within the industry, and a lack of skilled personnel for AI integration were the other important selected challenges by the survey respondents. Also, Oluleye, Chan, and Antwi-Afari [34], highlighted the challenges associated with construction's cost-intensive and slow innovation processes. Furthermore, a few survey respondents highlighted the challenges of 'not being integrated by BIM and GIS', respectively. The reason can be their uncertainty about the perceived manageability of integrating AI with BIM and the GIS. Lastly, only 2% of the survey respondents noted the challenges of working against current building practices and businesses. It demonstrates a shift toward recognizing the importance of innovative technologies by construction professionals to achieve sustainability.

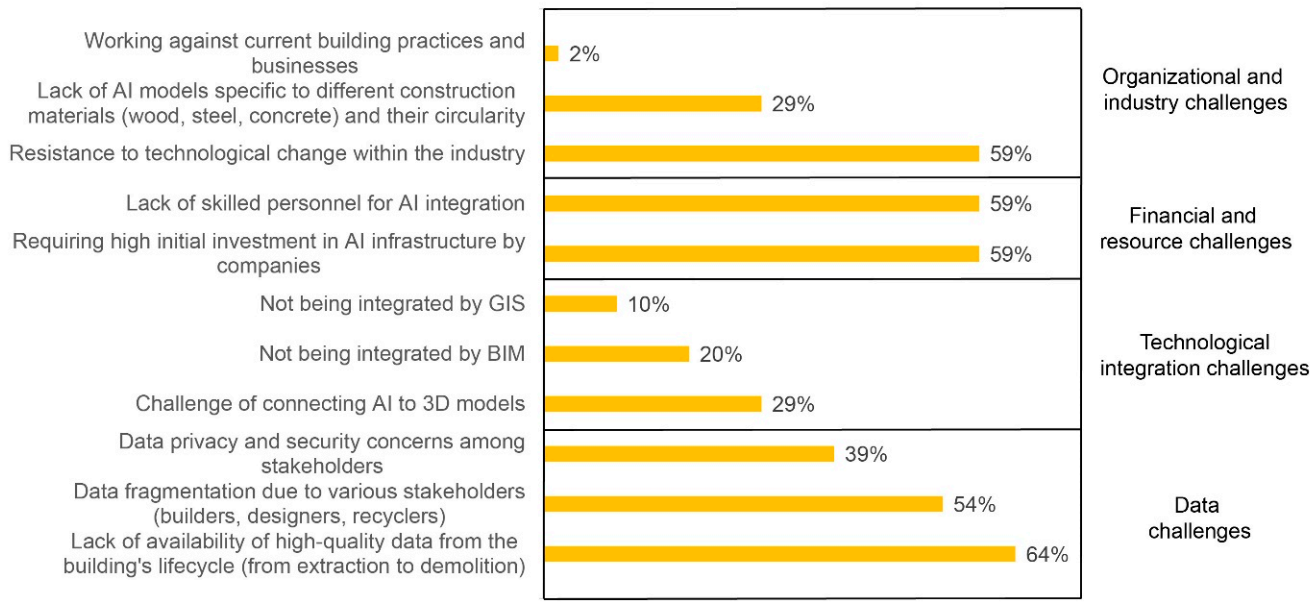


Figure 4. The percentages of potential challenges and their categories for implementing AI to promote CE in timber construction, based on survey responses.

The percentage figures shown in Figure 4 aligned with the challenges previously identified and reflect the confirmatory results, except for four challenges. These four challenges—the lack of availability of high-quality data from the building's lifecycle, the challenge of connecting AI to 3D models, the lack of AI models specific to different construction materials and their circularity, and not being integrated by the GIS—reflect the exploratory results. These four challenges are considered novel because they have not been discussed in prior studies.

Based on the survey analysis, the financial and resource challenges category was chosen as the most selected category related to its challenges by the survey respondents. Furthermore, the second most important category was data challenges, followed by organizational and industry challenges and technological integration challenges. The reason for selecting the financial and resource challenges category as the most selected category is the uncertainty of its economic feasibility. With the integration of BIM and GIS with AI, timber construction processes are enhanced by facilitating real-time monitoring and enabling more efficient project planning (refer to Interviewee 8). This interviewee addressed the possible challenge of integrating AI and BIM models by outlining,

> *"If you've got a good BIM model to start with when you create like the digital twin of the building and then by pairing that model with the images and the drone surveys and the geospatial orientation, it can probably be ok".* *(Int #8)*

According to the survey analysis, AI is still not widely adopted for construction specifically CE purposes. While AI is expected to offer many benefits to companies, 80% of survey respondents stated that AI is not currently used by their companies. Just half of those using AI use it specifically for CE purposes. As a result, AI implementation in the construction industry is not keeping pace with its potential benefits. Based on the survey results, those who use AI for CE purposes noted that AI helps optimize their material usage and record their construction progress.

Moreover, some construction professionals are interested in utilizing AI applications to promote CE, while others view it as an expensive technology that limits its usability (based on survey analysis). The following Figure 5 indicates the survey respondents' willingness to use AI in construction to promote CE in the future. Figure 5 shows that 23% of participants are not planning to use AI with the current functionality soon due to a lack of clear benefit to them. For example, two survey participants provided more information on or examples of benefits required for AI-based applications:

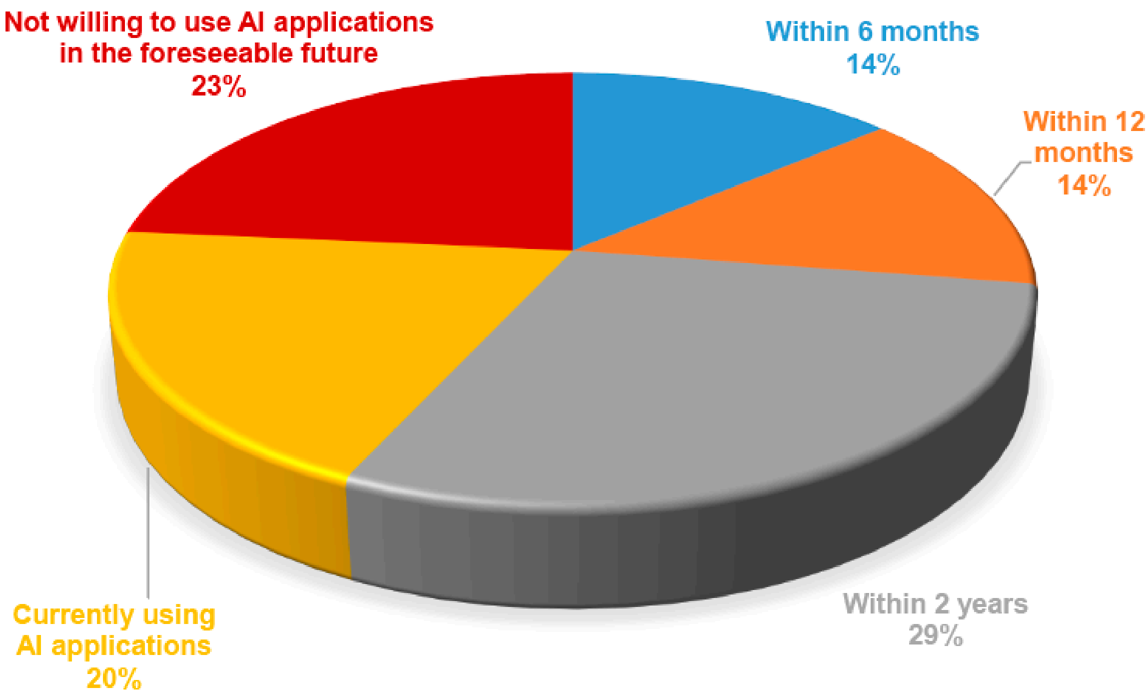


Figure 5. The willingness of the survey participants to use AI to promote CE in the near future.

> *"The actual construction companies will be very slow to update anything new unless it definitely is shown to provide a net benefit. For example, BIM has been pushed for years and has not become a mainstream software system because it is expensive and requires specific training for a nice-looking model that does not provide the returns on investment it promises".*

> *"The focus needs to be on providing the industry with something that provides real-world tangible results and not theoretical ideas that do not work in reality. Construction is a business so any innovations need to provide time or cost-benefit, or they will simply not be utilized".*

Figure 5 shows that AI's capacity has already been utilized by 20% of the survey respondents for various purposes. However, 57% of participants plan to uptake AI tools in the near future, considering their reliability and availability. A significant proportion of respondents planned to implement AI within the short term. This trend suggests a positive outlook for AI adoption in the construction industry. Increasing awareness and addressing economic and technological barriers such as data quality will likely lead to more firms adopting AI to drive CE initiatives over the next two years.

4. Discussion

This section is structured into four subsections to comprehensively address the research objectives of this study, including the contributions of AI applications to achieving a CE in timber construction (Section 4.1), potential benefits of integrating AI and a CE in timber construction (Section 4.2), potential challenges to implementing AI in timber construction to promote CE purposes (Section 4.3), and limitations and future directions (Section 4.4).

4.1. Contributions of AI Applications to Achieving CE in Timber Construction

The first research objective of this study was to analyze the potential contributions of AI applications in advancing a CE within timber construction. Based on the findings (Table 3), ML is a key subset and application to implement different AI functions obtained in this study to promote a CE. ML algorithms, for instance, allow engineers to analyze vast amounts of data from previous projects for timber structural engineering (refer to Interviewee 7). A reduction in timber construction costs and resource consumption is achieved by identifying efficient design options (refer to Interviewees 3 and 7).

The interview results show that the "AI-driven circularity process automation" represents a significant advancement over traditional timber processes by enabling the automation of more complex and cognitive tasks. Based on the opinions of interviewees, seven key complex tasks were identified. Examples of complex tasks were analyzing vast amounts of data, generating design options, automating the quality inspection of timber materials and components, predicting timber material requirements, automating workflows and processes, suggesting timber reuse options, and automating defect detection. Analyzing vast amounts of data as a complex task was supported by Interviewee 1, who mentioned, "AI has streamlined our project planning by analyzing vast amounts of data quickly and providing optimal scheduling recommendations". Generating design options as another complex task was supported by Interviewee 2, who mentioned, "AI tools help generate multiple design alternatives, taking into account various constraints and requirements". Automating the quality inspection of timber materials and components as another complex task was supported by Interviewee 1, who mentioned, "We have integrated AI to automate the inspection process, which not only speeds up the work but also ensures a higher level of accuracy". Predicting timber material requirements was another complex task supported by Interviewee 2, who mentioned, "AI's predictive analytics capabilities help us forecast material requirements and avoid shortage". Automating workflows and processes as another complex task was supported by Interviewee 3, who mentioned, "It looks mostly trying to create automated workflows for analysis and for carrying out data through the project". Suggesting timber reuse options as another complex task was supported by Interviewee 4, who mentioned, "given a certain structure, [AI] can guess the amount of timber in it. And based on those estimations, a different application use can be suggested". Finally, automating defect detection as another complex task was supported by Interviewee 7, who mentioned "using a camera to collect the data and using a computer vision model to detect particular things such as defects".

Based on the opinions of interviewees, three key cognitive tasks were identified. The examples of cognitive tasks were providing optimal design recommendations, answering common queries and providing guidance, and identifying timber components' features. Providing optimal design recommendations as a cognitive task was supported by Interviewee 3, who mentioned, "We do use some algorithms to work out the best design layouts". Answering common queries and providing guidance as another cognitive task was supported by Interviewee 2, who mentioned, "The AI-driven virtual assistants we have employed can answer common queries and provide guidance to our team members". Lastly, identifying timber components' features, such as identifying the hole location for using timber connections, was another cognitive task. This is supported by Interviewee 10 who mentioned that "automatically detecting where the edge is and then automatically saying ok, therefore, the holes need to be here". By identifying the hole location for timber components, prefabricated timber components will be deconstructed more efficiently at the end of the timber buildings' use.

Based on the findings above, AI was perceived to have the greatest impact on optimizing building designs. Another study conducted by Oluleye, Chan, and Antwi-Afari [34], supported this impact by highlighting the opportunity to plan the disassembly as an optimization of design. The survey respondents chose AI assistance in generating initial building layouts and floor plans and analyzing energy-efficient design strategies as the most impacted design tasks performed by the AI. Recommending sustainable and cost-effective material choices and optimizing building orientation and materials were chosen as less impacted design tasks performed by the AI. Based on the study conducted by Aziz et al. [49], AI is used to select among different materials with circularity characteristics with a set of constraints. A study conducted by Lu et al. [50] stated the role of AI and ML in minimizing waste by estimating the building construction waste. Minimizing resource usage and tracking the sustainability of construction materials were also important.

4.2. Potential Benefits of Integrating AI and CE in Timber Construction

The second research objective of this study was to identify the potential benefits of integrating AI and a CE in timber construction. The findings indicated the key benefits in three categories: environmental and resource efficiency, operational and project efficiency, and economic and business innovation (Section 3.2).

Reducing construction waste, lowering energy consumption, and enhancing project planning and scheduling were the most important benefits of integrating AI for CE purposes, based on the survey data (refer to Figure 3). Interviewee 9 supported the reduction of construction waste as a potential benefit of using AI by mentioning "*applying AI within a business to optimize a flow in a way that reduces the overall waste of the system*". Studies such as those by Gao et al. [51] demonstrate that ML models can forecast material requirements and reduce excess material procurement, contributing to lower waste levels.

Another interviewee (Interviewee 3) supported the lower energy consumption as a potential benefit by mentioning, "*I think it is just a matter of time until you have full AI-designed buildings. And I'm sure this would probably be more effective from an energy point of view*". Moreover, Interviewee 9 supported the enhanced project planning and scheduling as a potential benefit by mentioning that "*a lot of plans and schedules [tasks], especially for logistics and supply chain considerations can be conducted*". Based on the survey analysis (Figure 3), the survey respondents highlighted the impact of AI on analyzing data on existing building materials and recommending suitable reusing options for providing the circularity of products and materials. There are some potential future opportunities for AI to achieve circularity purposes in timber construction. Based on the interview findings (Section 3.2), Interviewee 8 offered an opportunity to provide a way for AI to integrate well with embodied Carbon in Construction Calculator (EC3) libraries to optimize the design by recommending changes to that. This opportunity provides the important benefits identified above. Moreover, enhanced project planning and scheduling benefits will be obtained by providing an AI engine to systematically feed into every stage of the project (refer to Interviewee 9).

Utilizing AI algorithms in timber construction at the design stage provides the advantages of accuracy, productivity, flexibility, and modeling capability. As an additional contribution to timber construction, AI contributes to the deconstruction and reuse capabilities at the design stage by detecting the characteristics of the components and optimizing the use of timber resources (refer to Interviewee 2). AI-driven optimization in material selection can significantly enhance resource efficiency by recommending materials with high recyclability and reusability, as supported by findings from Jogarao et al. [52]. Based on the interviewee's explanation (Interviewee 7), as timber components are deconstructed, computer vision is used to assess their visual properties and structural integrity.

The potential benefits of implementing AI for CE purposes in timber construction were not addressed in other similar studies. This study categorizes the potential benefits and provides unique contributions to the existing literature. Wilson et al. [53] investigated the AI implications with the CE specifically for reverse logistics rather than the construction process addressed in our study. Roberts, Zhang, Bariach, Cowls, Gilburt, Juneja, Tsamados, Ziosi, Taddeo, and Floridi [30] examined the role of AI in transitioning toward CE by analyzing its ethical risks. However, our study identified practical benefits obtained by the integration of AI for CE purposes. Several benefits have been identified, including energy efficiency, waste reduction, and a better ability to plan projects, which serve as clear incentives for timber construction companies to invest in AI. These findings related to newly examined benefits reflected the exploratory results.

4.3. Potential Challenges to Implementing AI in Timber Construction to Promote CE Purposes

The third research objective of this study was to uncover potential challenges to implementing AI in timber construction to promote CE purposes. Eight challenges were obtained from the interview results (Table 4). Furthermore, three more key challenges were identified through the survey responses (Section 3.3). These 11 challenges were categorized into four main categories (as illustrated in Figure 6): data challenges, technological integration challenges, financial and resource challenges, and organizational and industry challenges. Each category includes specific challenges and potential research directions to address them. The category of data challenges included the lack of availability of high-quality data from the building's lifecycle, data fragmentation due to various stakeholders, and data privacy and security concerns among stakeholders. The technological integration challenges category included the challenge of connecting AI to 3D models and not being integrated by BIM and the GIS. The financial and resource challenges category included the lack of skilled personnel for AI integration and the high initial investment required by companies in AI infrastructure. Lastly, the organizational and industry challenges category included the lack of AI models specific to different construction materials and their circularity, resistance to technological change within the industry, and working against current building practices and businesses. Based on the survey analysis (Figure 4), the financial and resource challenges category was chosen as the most selected category. Moreover, the lack of availability of high-quality data from the building's lifecycle, requiring high initial investment in AI infrastructure by companies, resistance to technological change within the industry, and a lack of skilled personnel for AI integration were the highest identified challenges for implementing AI to promote a CE. These challenges were supported by the interviewees' responses (Section 3.3). Interviewee 8 highlighted the lack of availability of high-quality data as an important challenge by mentioning that "*the data is available, but the consistency and quality of the data are questionable*". Interviewee 7 highlighted the requirement of high initial investment as an important challenge by mentioning that "*these projects cost huge amounts of money*". Another interviewee (Interviewee 7) highlighted the resistance to technological change as an important challenge by mentioning that "*construction is such an old-fashioned or traditional industry, very resistant to change*". Finally, Interviewee 10 highlighted the lack of skilled personnel for AI integration as an important challenge by mentioning that "*we don't have many people that know about both AI and construction*". Interviewee 6 said, "there are no large datasets to draw on to help with the design process, so a lot of architecture and engineering practices are now going through the process of standardizing and storing data".

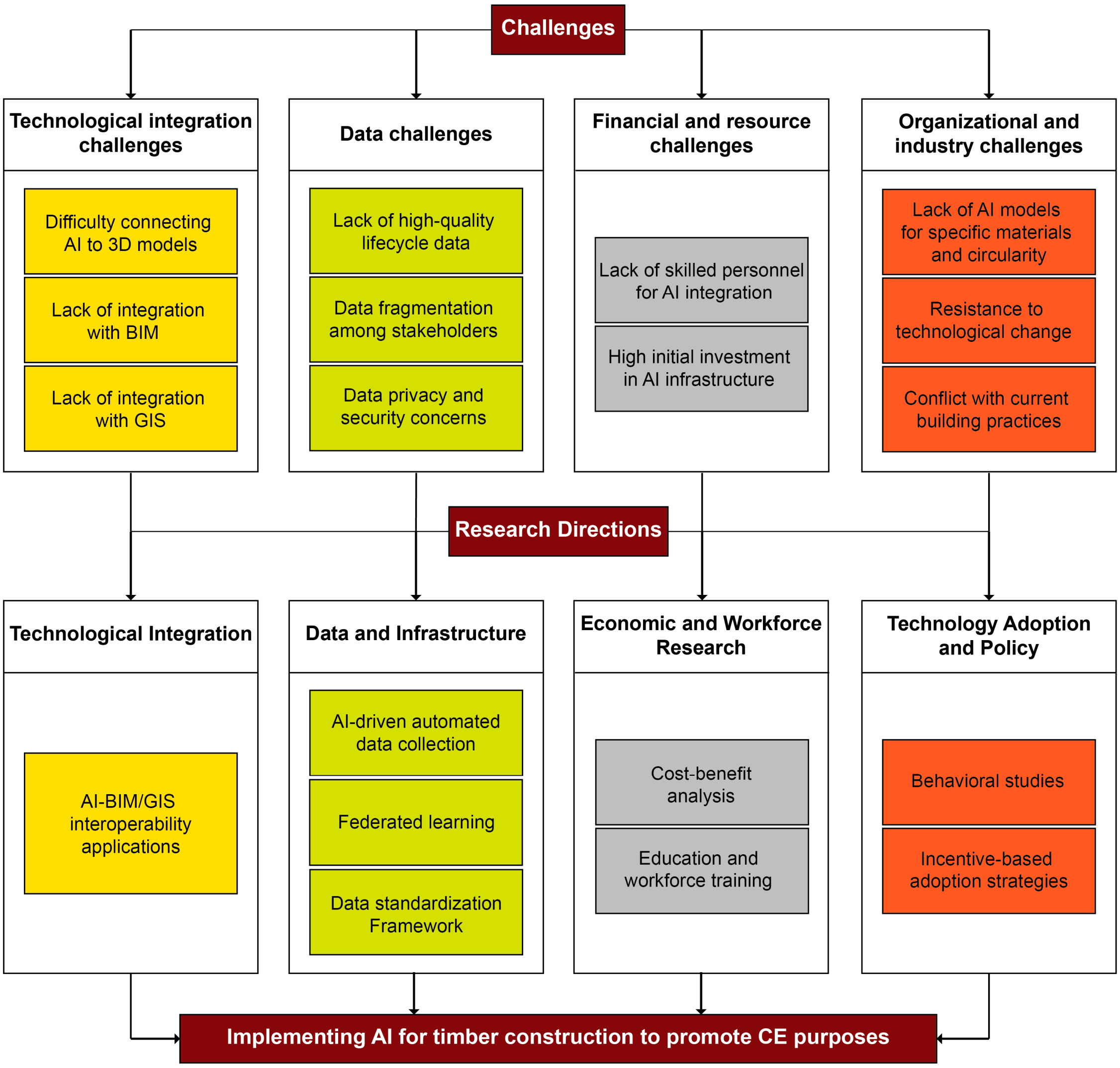


Figure 6. Challenges and research directions in implementing AI for timber construction to promote CE purposes. Note: CE: circular economy, AI: artificial intelligence, BIM: building information modelling, and GIS: geographic information system.

The lack of standardized data formats and data-sharing frameworks hinders AI's ability to analyze building lifecycle data effectively. Addressing this issue requires industry-wide standardization efforts and policy interventions. Additionally, policies that incentivize data-sharing agreements among stakeholders can mitigate data fragmentation challenges. Establishing a national centralized data repository, as suggested by Interviewee 6, would further support AI applications by providing reliable datasets for training ML models.

Government initiatives promoting open data policies, such as those observed in the European Union's digital construction strategies [54], could serve as a model for Australian timber construction companies. These policies encourage structured data collection and facilitate AI integration into circular construction workflows. By incorporating such strategies, the industry can overcome current data challenges and fully leverage AI's potential to enhance circularity in timber construction.

Despite the opportunities AI presents for advancing CE practices in construction, its adoption in Australia has been relatively gradual [55]. This can be attributed to the barriers mentioned above (Figure 6). Additionally, the relatively limited scale of Australia's timber construction sector has constrained market demand and investment opportunities, reducing incentives for innovation and further delaying AI adoption. By recognizing these key issues, targeted solutions can be better aligned with Australia's unique construction landscape. To address the above challenges, policymakers and industry leaders should propose recommendations such as introducing financial incentives to encourage data sharing, supporting digital material tracking systems, and promoting AI-integrated deconstruction planning tools. To address the issue of limited and high-quality data, a participant proposed utilizing sensors for timber buildings to easily collect the necessary data. Moreover, other possible solutions discussed by participants are encouraging data sharing through incentives for construction companies, establishing a national centralized data repository, and the standardization of data collection. Given the relatively limited scale of Australia's timber construction sector, expanding AI applications to other construction materials, such as steel and concrete, could provide greater incentives for innovation and facilitate the broader adoption of CE strategies, such as reuse. For instance, AI-driven predictive analytics can support better deconstruction planning by analyzing historical project data and identifying optimal deconstruction sequences. Similarly, computer vision technologies can improve material sorting and quality assessment by recognizing material types and assessing material surface conditions through image processing techniques. AI tools, such as ML algorithms, can also optimize material reuse by predicting material lifespans and identifying components suitable for reuse.

As part of the practical recommendations from the interviewee responses (Section 3.3), targeted training programs have to be developed, collaboration among stakeholders has to be increased, and construction-wide data standards to close the key challenges in Australia require development. In order to solve the problem of lack of available and quality data, Interviewee 10 suggested using sensors for timber buildings to easily obtain the data. Other possible solutions discussed by Interviewees 10, 8, and 6 are encouraging data sharing through incentives for construction companies, establishing a national centralized data repository, and the standardization of data collection. Moreover, expanding AI applications beyond timber construction could help accelerate AI-CE integration across the broader Australian construction industry. For instance, AI tools could be employed to enhance CE strategies in steel and concrete structures by improving material recovery, deconstruction planning, and resource optimization. Additionally, integrating AI into circular supply chains—such as through automated inventory tracking, predictive maintenance systems, and digital material passports—could further support resource efficiency across various building types.

Construction is a traditional industry that is very resistant to change. One possible solution to this problem is to introduce AI to construction practitioners in small ways and prove its use cases and cost-effectiveness to persuade them to accept it. So, Australian timber construction companies have to consider a phased AI implementation strategy to minimize resistance to change and manage costs. To solve the high initial investment challenge, possible solutions include implementing cloud-based AI solutions and offering subsidies and grants by the Australian government. Finally, one possible solution is to encourage collaboration between academia and the construction industry to address the lack of skilled personnel. AI adoption is expected to grow in Australia in the next few years, and if these challenges are effectively managed, the timber construction industry will experience rapid transformation.

Based on the above solutions, addressing data challenges requires research on AI-driven automated data collection using IoT and sensors to improve material tracking and reuse potential in circular timber construction (as highlighted in [31]). Additionally, federated learning frameworks can be explored for enabling privacy-preserving data sharing in multi-stakeholder construction projects (as highlighted in [56]). The technological integration challenges highlight the need for AI-BIM/GIS interoperability applications that facilitate material passports to optimize CE purposes in timber construction (refer to Interviewee 8). To overcome financial and resource challenges, future research should focus on the cost–benefit analysis of AI-powered CE systems, including predictive maintenance and material recovery optimization (refer to Interviewee 2). Furthermore, education and workforce training programs are essential to equip construction professionals with digital skills for AI adoption in circular timber construction (refer to Interviewee 7). Finally, organizational and industry challenges can be addressed by conducting behavioral studies to identify adoption barriers and developing incentive-based adoption strategies to encourage AI integration in construction (as highlighted in [57]).

The AI challenges outlined above (despite the lack of availability of high-quality data from the building's lifecycle, the challenge of connecting AI to 3D models, the lack of AI models specific to different construction materials and their circularity, and not being integrated by the GIS), reflected the confirmatory results. Other studies previously identified these AI functions (e.g., [34]). In contrast, the percentages related to new challenges reflected the exploratory results. The aforementioned 11 challenges of implementing AI for CE purposes in the timber construction industry were not discussed entirely in other similar studies and this study offers a categorization of the challenges and provides unique contributions to the existing literature. Pathan, Richardson, Galvan, and Mooney [42] examined the intersection of AI and a CE in Ireland by providing practical examples. However, our study focused on Australian construction practitioners to provide more actionable recommendations for stakeholders within that context by providing challenges. Oluleye, Chan, and Antwi-Afari [34] conducted a systematic literature review to identify the challenges of applying AI in enabling CE implementation in construction. They identified challenges of applying AI for systemic circularity, such as data challenges and limited digital infrastructures. The identified challenges in our study were modified to the existing challenges in the literature. However, their study lacks empirical data from practitioners and our study provided a more comprehensive perspective grounded in real-world experiences by incorporating construction practitioners' perspectives. Furthermore, this study highlighted unexplored challenges, including the lack of high-quality data from the building's lifecycle and data fragmentation due to various stakeholders.

4.4. Limitations and Future Directions

The primary limitations of this study relate to the limited sample size and specific sample country. The focus of this study was on the Australian construction industry only, so the sample size may not be representative of the entire industry. In the future, a more diverse sample should be included to ensure the robustness, generalizability, and applicability of the results. Additionally, this study focused only on AI technology. ML, for example, can be investigated separately from other algorithms. According to the results of this study, it is recommended to develop and validate AI models customized for different construction materials and processes, not just timber construction. The construction industry could also gain insight into how AI integration affects CE outcomes through longitudinal studies. Further studies are required to examine AI's impact on the environment and economy in developing countries with significantly different markets and resource constraints.

5. Conclusions

This study aimed to examine the implications of integrating AI into the CE, by identifying the benefits and advantages of using AI to promote a CE in the timber construction sector. Reducing construction waste, facilitating the deconstruction process, and lowering energy consumption were identified as the most important benefits of integrating AI and a CE in timber construction. Incorporating AI into timber construction at the design stage provides the advantages of accuracy, productivity, flexibility, and modeling capability. Moreover, the lack of availability of high-quality data from the building's lifecycle, requiring a high initial investment in AI infrastructure by companies, resistance to technological change within the industry, and a lack of skilled personnel for AI integration were identified as the greatest challenges for implementing AI to promote a CE.

This study is the first of its kind to identify the potential benefits and challenges for the implementation of AI in circular timber construction. In addition to identifying these benefits and challenges, this study provides a novel structured framework for understanding AI's specific contributions to CE practices in timber construction, which has not been extensively explored in previous research. The novelty lies in the integration of AI-driven optimization with material reuse strategies, offering a new perspective on sustainable construction methodologies. Despite being in its preliminary stages, this study showcases much of the untapped potential of AI to address timber material reuse and to enhance the industry's operational efficiency and sustainability in timber construction.

As an exploratory effort, this study also captures industry perspectives on the challenges and benefits of integrating AI in circular timber construction. The study also underscores critical challenges, such as the financial and resource challenges, that impede the adoption of AI in timber construction. Ultimately, this study emphasizes how AI can take on a transformative role in driving CE initiatives. To create a more sustainable and resilient timber construction industry, this study lays the groundwork for future investigations and policy initiatives. Timber construction stakeholders must remain committed, adaptive, and vigilant to balancing economic growth with environmental stewardship through AI and CE. From a practical standpoint, the findings of this study can guide industry professionals, policymakers, and researchers in designing AI-driven solutions tailored to the unique challenges of circular timber construction. The insights provided can inform decision-making processes regarding AI investment, skill development, and regulatory frameworks, ensuring that AI adoption leads to tangible improvements in material efficiency and sustainability within the industry.

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