Delft University of Technology

Master Thesis

CME Projects & People

Machine Learning in Reusability Potential Assessment for Sustainable Renovation of Bridges and Quay Walls in Amsterdam

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Abstract

This thesis explores how Machine Learning (ML) can enhance the assessment of reusability potential in the sustainable renovation of Amsterdam's bridges and quay walls. As the city faces the urgent task of renovating large parts of its aging infrastructure, sustainable renovation strategies such as material reuse are gaining importance. However, assessing the reusability potential of existing structural components remains a complex challenge that is not only shaped by technical factors, but also by the influence of various stakeholders involved throughout the renovation process.

The research combines a literature review, stakeholder interviews, and the development of a machine learning model trained on data from 20 completed and ongoing bridge and quay wall renovation projects in Amsterdam. It examines both the technical data and stakeholder related insights, by investigating how technical factors, stakeholder roles and priorities affect reuse decisions. The main research question guiding this study is:

Main Research Question: *How can Machine Learning enhance the reusability potential assessment for the sustainable renovation of Amsterdam's bridges and quay walls?*

To answer this, the research addresses four sub-questions:

1. **What information and data are available for assessing reusability potential and preparing the pre-deconstruction audit; and how do different stakeholders influence the assessment of reusability potential?**
2. **Which factors are most important to stakeholders for reusability?**
3. **Which factors most effectively influence the successful assessment and application of material reuse in sustainable renovation projects?**
4. **How can machine learning models support reusability predictions in future projects?**

Extensive literature review and stakeholder interview results show that assessing reusability potential involves both technical data, such as material condition, inspection reports, and testing, and the influence of various stakeholders. Municipal authorities establish sustainability goals, engineering firms provide technical evaluations, and contractors assess feasibility. Decisions are also shaped by political priorities and public perspectives. However, challenges remain due to fragmented responsibilities and inconsistent data standards.

Stakeholders identified reuse policy, willingness to reuse, material quality and testing, and early stakeholder engagement as the most important factors for successful reuse. Balancing these organizational and technical elements is crucial in assessing reusability potential. These 4 identified factors were then used to collect data to train and test the machine learning model on.

Out of the 6 different ML techniques used to train and test the collected data from the Amsterdam bridges and quay walls, the Gradient Boosting showed the best predictive accuracy. The ML model results developed based on the 4 factors reveal that material quality and early stakeholder involvement have the greatest impact on actual reuse outcomes. These factors were the strongest predictors in the machine learning model, underscoring their importance in practical reuse success. Organizational factors like policy and willingness are still essential for enabling reuse but are less effective in a machine learning model due to less variation across projects.

The results from the machine learning model clearly show where to focus future efforts: the condition of materials and involving stakeholders early on are the most important factors for successful reuse. While this study mainly looked at technical and organizational aspects, including economic, environmental, and timing factors in future models could make reuse predictions even more accurate and comprehensive. For future uses of machine learning for reusability potential assessment, model usefulness increases when integrated into a wider ecosystem that includes city-wide reuse strategies, early design phase integration, live digital platforms linking reuse supply and demand, and collaborative data sharing. In this broader context, machine learning serves not just as a prediction tool but as a strategic asset to support circular renovation practices.

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Finishing this thesis also means closing off my time as a master's student. It has been a journey full of learning, challenges, and growth, and I am so grateful to everyone who helped me get to this point.

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1 Introduction

This chapter provides an overview of the purpose and context of this research, along with the structure of the report. Section 1.1 outlines the problem statement, highlighting the significance and relevance of this study. Section 1.2 elaborates on the research objective, introducing the main research question and its supporting sub-questions. Section 1.3 defines the scope and relevance of the research, while Section 1.4 concludes the chapter with a description of the report's structure.

1.1 Problem Statement

In historic city centers like Amsterdam, aging infrastructure has become a pressing challenge. Many of the city's bridges and quay walls, some of which are centuries old, now require urgent renovation or replacement due to overdue maintenance and the impacts of increasing urban activity, particularly from freight traffic. The demand on this infrastructure not only highlights structural concerns but also calls for innovative approaches that address the environmental and logistical complexity of large-scale urban renovation. In response, the municipality of Amsterdam has launched a comprehensive program to assess and, where necessary, restore approximately 200 kilometers of quay walls and 800 bridges. This effort aligns with broader societal goals, such as climate adaptation, energy transition, and circularity, and has led to partnerships between Amsterdam's public sector, researchers, and market parties. Among these collaborations, the Dutch Research Council (NWO) and Amsterdam jointly initiated the "Urban Bridges and Quay Walls" (Urbiquay) program, which is dedicated to finding sustainable and circular solutions to support the future resilience of urban infrastructure. This initiative brings together three major research projects that focus on monitoring structural integrity, environmentally friendly restoration, and closed-loop logistics solutions that prioritize reuse, reduce emissions, and respect cultural-historical values. Within this program, the Logiquay proposal addresses this by developing closed-loop logistics and multi-project control solutions to speed up renovations, improve oversight, and enhance sustainability, focusing on reusing materials, reducing transport, and lowering emissions (NWO 2024).

Supporting the aims of the Logiquay proposal, this research investigates how assessing reusability potential can contribute to sustainable renovation practices in urban infrastructure. By analyzing multiple projects, this study will identify key data and people factors influencing reusability potential. Leveraging machine learning, it seeks to pinpoint which factors most significantly improve outcomes in material reuse, with the goal of enhancing efficiency and minimizing waste. This research investigates: the types of information and data available for assessing reusability during pre-deconstruction audits; the roles of various stakeholders and their influence on reusability assessments; the key factors that contribute to successful material reuse in renovation projects through machine learning; and how machine learning can further be used to aid the reusability potential assessment. In exploring these dimensions, this research contributes to Amsterdam's overarching ambition to develop sustainable, reusability methodologies that can serve as scalable models for other municipalities facing similar infrastructure pressures. By advancing our understanding of reusability potential in renovation projects, this study supports the broader goals of sustainable urban development and future-resilient infrastructure.

1.2 Research Objective

This study aims to improve the understanding of reusability potential in sustainable renovation practices by utilizing Machine Learning. It will explore the technical side such as data and information for reusability potential assessment, the people side by taking a look at the stakeholders and their interactions, and these technical and people factors influencing material reuse to finally create a machine learning model that includes these factors and identify the most influential factors to reusability potential and predict reusability potential of future projects.

1.2.1 Main Research Question

The main research question guiding this study is:

"How can Machine Learning enhance the reusability potential assessment for the sustainable renovation of Amsterdam's bridges and quay walls?"

1.2.2 Sub Research Questions

This main question will be addressed through the following sub-research questions, each corresponding to a specific objective:

1. **What information and data are available for assessing reusability potential and preparing the pre-deconstruction audit; and how do different stakeholders influence the assessment of reusability potential?**

    - Objective: Assessing the available information and data for reusability potential and preparing pre-deconstruction audits, starting with existing historic data in the City and manual scans by Logiquay partners such as Nebest. This objective seeks to identify the types of data and information required for preparing the pre-deconstruction audit to assess material reuse potential for the Amsterdam bridges and quay walls renovation. Additionally, the role of stakeholders (contractors, engineering firms, city experts, and citizens) will be explored to understand how they influence the reusability assessment process and how they interact with the data.

2. **Which factors are most important to stakeholders for reusability?**
   - Objective: Based on the information gathered in the first question regarding the available data and information for assessing reusability, this objective aims to identify the factors stakeholders consider most important for reusability in renovation projects through interviews with stakeholders. Later in these factors will be assessed in sub-question 3.
3. **Which factors most effectively influence the successful assessment and application of material reuse in renovation projects?**
   - Objective: Identifying key factors that influence the successful application of material reuse in sustainable renovation projects by creating a machine learning model. This objective combines both technical and people-related factors from sub-questions 1 and 2 to explore those that most effectively drive successful material reuse.
4. **How can machine learning be used for predicting reusability potential in future projects?**
   - Objective: The machine learning model from question 3 can be further investigated to be used as solution for this question by looking at how it can be used for estimating the reusability potential for future projects, as well as looking into generative capabilities for reusability potential assessment.

1.3 Scope and Relevance

This research focuses on assessing reusability potential in the renovation of bridges and quay walls in historic city centers like Amsterdam. By examining multiple infrastructure projects, the study will identify the data and qualitative factors that influence material reuse, including the roles of stakeholders and methods for organizing reusability information. Using machine learning, the research will analyze key factors that contribute to successful material reuse, aiming to improve efficiency, reduce waste, and enhance sustainability in circular renovation practices. The findings will support the Logiquay project by providing insights for optimizing circular logistics and reducing emissions in urban infrastructure renovation projects.

The renovation of aging infrastructure, such as bridges and quay walls in cities like Amsterdam, presents significant challenges in terms of sustainability and resource management. While circular approaches that prioritize material reuse are gaining traction, there is a clear research gap in effectively assessing and managing reusability potential in large-scale urban infrastructure projects. Existing practices often lack comprehensive data, clear frameworks for stakeholder collaboration, and structured methods for organizing reusability information. This research aims to address these gaps by identifying key factors that influence material reuse and proposing methods to improve data collection, stakeholder engagement, ultimately contributing to more effective and sustainable renovation practices by applying Machine Learning.

1.4 Report Structure

The structure of this thesis is as follows: Chapter 2 details the research methodology, elaborating on the approaches used in this research for gathering data, analyzing, and evaluating data relevant to assessing reusability potential. Chapter 3 presents the literature review, systematically exploring theoretical findings related to sub-questions 1 and 2 as a background study for the interviews. Chapter 4 provides the semi-structured interview results, offering insights about the data and stakeholder roles and their impact on reusability assessments, thereby answering sub-research question 1 and 2. Chapter 5 integrates theoretical and practical findings to identify key factors influencing material reuse and introduces a machine learning model to explore these factors, addressing sub-research question 3. Chapter 6 delves into how machine learning can further enhance reusability potential assessments, thereby answering sub-research question 4. Chapter 7 provides the discussion, and Chapter 8 concludes the study by answering the main research question.

2 Methodology

The following methodology was used to address the research questions: a combination of literature review, case studies, and interviews, and qualitative comparative analysis using machine learning. Here, an overview is given for the research questions and their methods, followed by more in-dept information about the literature review, case study and interviews, and the qualitative comparative analysis. Subsection 2.1 details the methods applied to each research question. Subsection 2.2 focuses on the literature review. Subsection 2.3 describes the case studies and interviews. Finally, Subsection 2.4 outlines the QCA methodology using machine learning to analyze the factors affecting reusability potential.

2.1 Methods per research question

Each research question has been addressed with corresponding methods found in table below:

Research Question	Methods
1. What information and data are available for assessing reusability potential and preparing the pre-deconstruction audit, and how do different stakeholders influence the assessment of reusability potential?	Literature review: Identify types of data used in pre-deconstruction audits and identify key stakeholders influences. Case studies: Analyze real-world projects using existing data and manual scans from Logiquay partners (e.g., Nebest) and examine stakeholder involvement in the renovation projects. Interviews: Gather insights from stakeholders involved in the Amsterdam bridges and quay walls renovation.
2. Which factors are most important to stakeholders for reusability?	Interviews: Collect input from stakeholders (contractors, engineers, city experts) on which factors they consider most important for reusability in renovation projects.
3. Which factors most effectively influence the successful assessment and application of material reuse in sustainable renovation projects?	QCA using machine learning: Identify and compare factors impacting material reuse. Analysis of findings: Use data from Questions 1 and 2 to identify key conditions for successful reuse. Case study reviews: Focus on finished sustainable projects to validate findings.
4. How can machine learning be used for predicting reusability potential in future projects?	Analysis of ML model findings: Findings from Question 3, being the ML model, can be used as a result for future use. Stakeholder insights: Incorporate feedback from interviews on structuring ML models for practical use.

Table 1: Methods per research question.

The methodology for this research is structured to address the main research questions through a combination of literature review, case studies, interviews, and machine learning-based qualitative comparative analysis (QCA). The flowchart below illustrates the sequential steps of the research methodology and how each part corresponds to the respective research sub-questions.

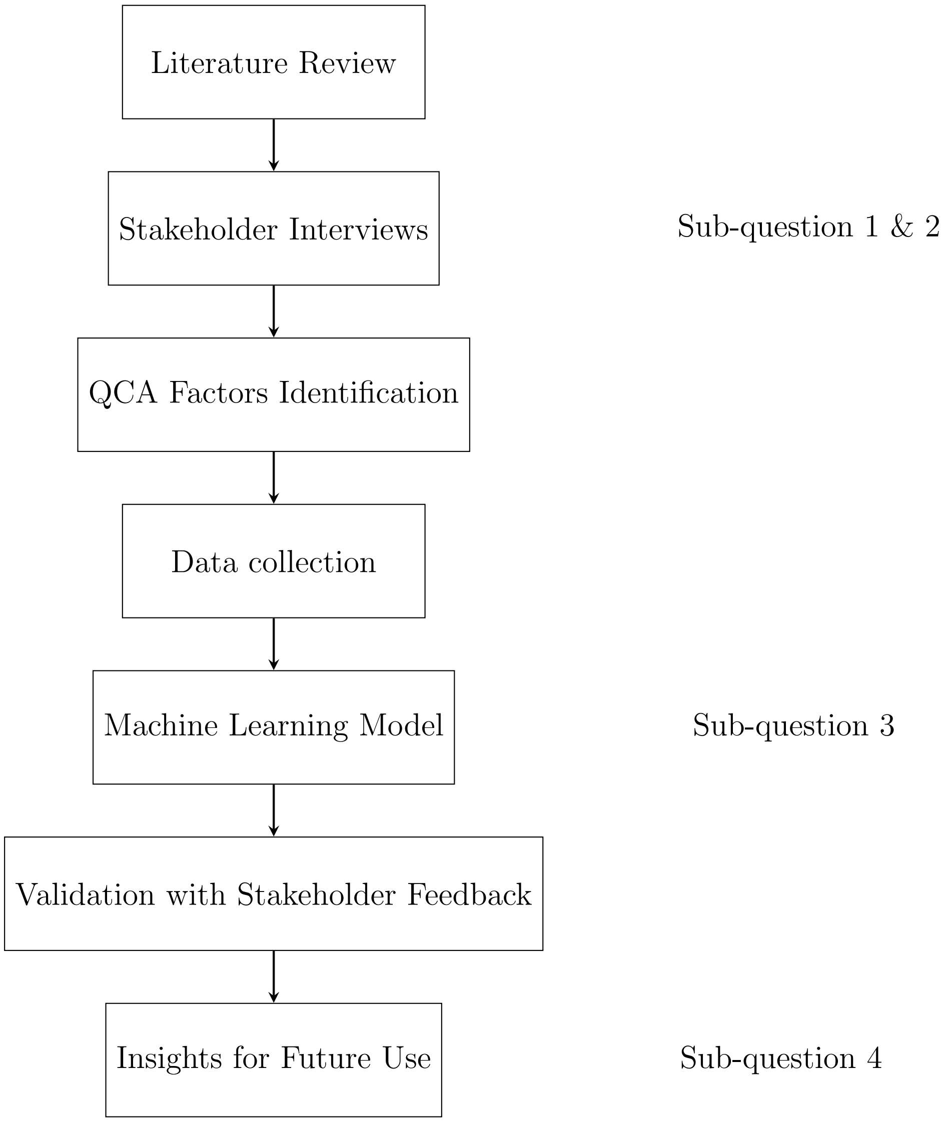

Figure 1: Methodology Flowchart with Research Questions

2.2 Literature review

Firstly, a literature review has been conducted, structured around key areas relevant to each sub-question of the research. The first area focuses on pre-deconstruction audits and the essential data and information related to the audits. This involves reviewing studies on sustainable renovation and material reuse to understand what data is needed to assess reusability potential early in the deconstruction process.

Next, the literature review explores stakeholder roles in the reusability assessment. Understanding the dynamics of stakeholder collaboration and data sharing is crucial for guiding the

interviews and identifying key contributors who influence the effectiveness of material reuse in renovation projects.
The third area of focus analyzes factors that influence successful material reuse. By examining existing literature, the review highlights factors that play a role in the effective management of materials throughout the renovation lifecycle. This helps to form the basis for a qualitative comparative analysis machine learning model to identify the most important factors for reusability assessment.
Lastly, the literature review examines how machine learning and AI can be used to identify patterns in data to understand how key factors influence certain outcomes, highlighting its potential to enhance practices in reusability assessment and the built environment.

2.3 Case studies and Interviews

Case studies as a research method involve an in depth analysis of real situations within a specific context, this includes both quantitative and qualitative data (Zainal 2007). While case study as a method may not be suitable for completely addressing research question 1,2 and 3 directly, it still plays a valuable role in contextual understanding to enhance the overall research findings and enhance the interviews. Multiple cases (both completed and ongoing projects) from the Amsterdam bridges and quay wall renovations were selected to provide a comprehensive analysis of the research topic. By looking at multiple projects, different perspectives can be gained from the real life Amsterdam bridges and quay wall renovations and an overall broader understanding of the research questions can be achieved (Gustafsson 2017). Data collection about the cases is intended through interviews. Even though it is known that a disadvantage of working with case studies is the involvement of a lot of documentation work (Zainal 2007), it is important to note that in this research, the case study is not the primary methodology for addressing research questions 1 and 2. Instead, it is used as a complementary approach to provide the context and enhance the interview process.

To gather qualitative data and gain valuable perspectives from actual stakeholders involved in sustainable construction projects, in-depth interviews were conducted (Weiss 1994). These interviews helped address research questions 1, 2, (and 3). For a comprehensive understanding, a semi-structured interview methodology was selected. This allowed for a balance between a predetermined fixed set of questions and the flexibility to delve deeper into specific topics as the conversation emerged. This semi-structured approach provides more freedom to allow in-depth questions compared to a fully structured interview, as there were opportunities to ask for clarification from the respondents about their answers and insights. While interviews can be more time-consuming compared to other research methods, by using the semi-structured approach with a fixed and consistent topic guide, time was saved in selecting questions for different respondents. This approach ensured good consistency in data collection and supported an effective qualitative analysis (Knott et al. 2022).

To gain different perspectives, the interviewees, who were stakeholders involved in the renovation of the Amsterdam bridges and quay walls, consisted of people from different roles in the project such as contractors (SOK Kademakers), engineering firms (SOK IDs), and city experts (Alshenqeeti 2014; Group 2019). 5 interviews were conducted to gather insights and 2 more were conducted as validation interviews with experts from the municipality. To ensure diverse perspectives, around 2 individuals were interviewed from each stakeholder group, considering the different actors within the broader context of the Amsterdam bridges and quay walls.

The interview structure for sub-questions 1 and 2 is provided in Appendix A1.

2.4 Qualitative Comparative Analysis using Machine Learning

To address sub-questions 3 and 4, a fuzzy set Qualitative Comparative Analysis (QCA) was conducted to compare various sustainable renovation projects. This analysis focused on both technical and stakeholder-related factors identified from the literature and findings of the first two sub-questions. Using Python (with libraries such as pandas), the study applied machine learning techniques like multivariate regression, random forest, and correlation models to reveal patterns and prioritize factors that most significantly affected reusability potential. The analysis included multiple projects sourced from case studies and interviews, while additional cases were selected through Logiquay partners and a literature review of circular renovation projects.

The process for the QCA machine learning model can be summarized as the flowchart in Figure 2.

2.4.1 Identifying the Factors

The first step in building the ML model was to determine the factors that might influence the reusability of materials. These factors were selected based on interviews with professionals and stakeholders involved in sustainable renovation projects and answers to sub-questions 1 and 2. Through these interviews, participants provided insights into the data they used and the key variables they believed impacted reusability potential. The factors included technical aspects surrounding project data and information, as well as stakeholder-related factors like collaboration and community engagement. Selecting factors that are consistent across all projects was considered unlikely to effectively assess reusability, as variability is key to meaningful analysis.

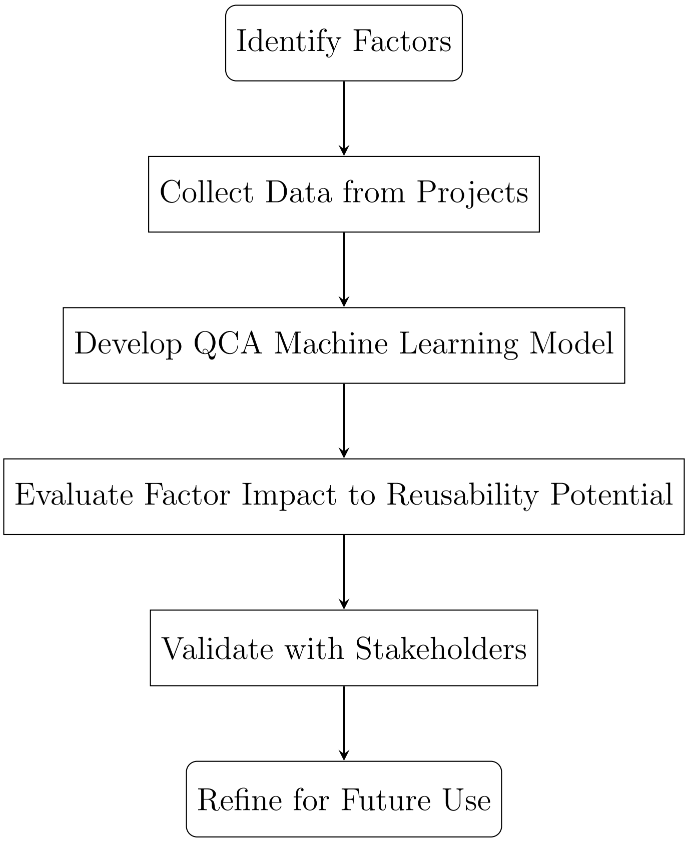

Figure 2: QCA Machine Learning Model method process flow

Additionally, the chosen factors needed to be independent; for instance, including both material age and quality as separate factors would have been redundant, as age directly influences quality.

2.4.2 Data Collection

Once the relevant factors had been identified, the next step involves data collection for multiple projects. This data was gathered from different related projects from the Amsterdam bridges and quay walls and interviews with stakeholders, with additional data being sourced from Logiquay partners such as Nebest. The number of projects needed to be collected depends on the range of factors identified. For k factors, the number of projects in the analysis should be 2^k, where k is the number of factors (Elliott 2013). In the case of this research, for 4 factors the minimum number of projects for which data should be collected in the QCA was 16.

The collected data included the factor data for each of the considered factors for the ML model and the reusability potential for each project. This data collection ensured that the ML model is built on a solid foundation of real-world data.

2.4.3 Building the ML Model

With the data in hand, the ML model was developed. The model focuses on understanding how various factors combine to influence the reusability potential.

- Training the Model: The ML model was trained using the collected data, where each factor and its corresponding data from different projects were processed. The modellearned to identify patterns and correlations between the factors and reusability potential.

- Evaluating Factor Impact: After training, the model provided insights into how strongly each factor influences reusability potential. For instance, the model might reveal that "material quality" and "stakeholder collaboration" are the most significant factors for increasing reusability, while "regulatory support" might have a lesser effect.

Once the QCA model has been trained and the factors are evaluated, the model is able to predict the reusability potential of future projects based on the factors it has learned. This predictive capability is one of the key strengths of using machine learning.
For example, if a new renovation project is being considered, the model can assess the project's characteristics (through the factors hat are the input to the ML model) and predict the amount and how likely it is that materials from the project will be reused. This allows for informed decision-making based on data-driven predictions.

2.4.4 Validation and Stakeholder Feedback

After the model is trained and the QCA is completed, the findings were validated through stakeholder feedback, gathered via interviews. This validation phase ensures that the results are relevant and whether the factors identified, and the model's predictions, align with practical experience. This validation phase ensures the applicability of the QCA model.

2.4.5 Future Use

Finally, in response to sub-question 4, insights from stakeholders helped refine the model further, ensuring its utility in future projects. Feedback on how to improve or expand the model in future renovation projects inform how machine learning can optimize reusability assessments over time. Stakeholder feedback brings insights on adjust the model's structure, the factors included, and how predictions are made, making it a more effective tool for sustainable renovation decision-making.

Using the machine learning model, this methodology provides a quantitative approach to determining the factors that most significantly influence the reusability potential in sustainable renovation projects. The predictive capabilities of the model and its adaptability to new projects will make it a valuable tool for the sustainable renovation of urban infrastructure, particularly in the context of Amsterdam's bridges and quay walls.

3 Literature Review

In the following literature review research papers related to the topic of reusability potential in circular renovation projects. Subsection 3.1 covers pre-deconstruction audits, highlighting their role in waste reduction and material recovery. Subsection 3.2 analyzes the influence of stakeholders in the Amsterdam quay wall and bridge renovations. Subsection 3.3 examines various factors affecting reusability found in literature. In Subsection 3.4, we explore the method of Qualitative Comparative Analysis (QCA) with machine learning (ML). Finally, Subsection 3.5 identifies gaps in the literature,

3.1 Pre-deconstruction audits

Pre-demolition audits are essential tools for enhancing material recovery and improving construction and demolition (C&D) waste management within the Circular Economy (CE) framework. Conducting these audits before any demolition or renovation allows for a thorough assessment of on-site materials, helping to identify recyclable and reusable components (European Commission 2018). This process reduces construction and demolition waste (CDW) by diverting materials toward recycling and reuse streams instead of disposal (European Commission n.d.; Da Silva 2023).

These audits focus on collecting data on the types, quantities, and potential treatment paths for building materials, critical for planning the deconstruction process. This data enables project managers to prioritize environmentally friendly methods based on the five-tier waste hierarchy (European Commission 2018). Defining specific site waste management plans through audits helps improve material recovery efficiency, reduce waste, conserve resources, and minimize the carbon footprint associated with renovation and demolition (Rašković et al. 2020; Da Silva 2023).

Beyond waste management, pre-demolition audits improve worker safety by identifying hazardous materials that should be removed first, reducing the risk of contaminating recyclable materials and enhancing on-site safety standards (Wahlström et al. 2019). Audits also provide economic benefits by increasing the amount of material that can be reused or sold, generating value for contractors and clients through reduced disposal fees and material costs (García et al. 2017; Da Silva 2023).

Literature shows that pre-demolition audits offer a structured approach for sustainable waste management, worker safety, and economic gains in construction projects which is relevant for this research as well.

3.2 Stakeholder Analysis

In his stakeholder analysis, Heuvel (2024) provides valuable insights into the roles, and influence of key stakeholders involved in 'Programma Bruggen en Kademuren (PBK)' the project of Amsterdam's bridges and quay wall infrastructure.

The stakeholders involved in the renovation project are categorized into two main groups: general stakeholders and professional stakeholders. General stakeholders include citizens, visitors, and individuals who depend on the city's infrastructure for their work. These groups are typically non-professional stakeholders, relying on the infrastructure for daily use or business activities, such as taxi drivers or small shop owners. Professional stakeholders are those directly involved in the operation and maintenance of the infrastructure. These include companies that rely on the infrastructure, like large enterprises or theatres, which are consulted earlier in the planning stages. Other professional stakeholders are companies integral to the city's infrastructure, such as GVB (public transport providers) and energy companies (Heuvel 2024).

The municipality of Amsterdam is the largest and most complex stakeholder, owning most of the quay walls and bridges. It plays a significant role in decision-making, holding the power to award permits and manage the project, with authority vested in the stadsdeelregisseur (local district director). The municipality's influence stems from its control over the city's infrastructure and its decision-making authority, making it central to the project's development and implementation. Heuvel (2024) references theoretical frameworks that underscore the value of stakeholder involvement, particularly in the strategic phase of projects. Early engagement is recommended as a means to reduce resistance and enhance the perceived value of the project among stakeholders. Moreover, Heuvel (2024) advocates for a shift in stakeholder management practices, suggesting that municipalities should prioritize the involvement of citizens and infrastructure users during the strategic phase.

When it comes to material reuse, effective collaboration is crucial. The challenges of reusing materials—such as economic, environmental, organizational, and regulatory factors—require all stakeholders to work closely together. Bellini et al. (2024) highlights that involving architects and consultants early on in the process is key for creating an information-driven approach to material reuse in the supply chain.

The integration of circular economy principles, such as optimizing resource use and promoting recycling, also depends on strong stakeholder engagement. According to Adebayo et al. (2024b), strategies like stakeholder analysis, transparent communication, and collaborative decision-making are essential to align different interests and encourage the adoption of circular economy practices. Overcoming challenges like resistance to change and the complexity of coordinating various stakeholders can be addressed with change management techniques and fostering a supportive organizational culture.

Moreover, challenges specific to material reuse, such as the availability, quality of materials, and non-standardization, require unconventional partnerships and improved information exchange among stakeholders. As Matrai (2019) points out, the willingness to compromise, joint risk-sharing, and the provision of additional resources (such as time, financial support, and education) are crucial for overcoming the institutional and contractual barriers that often arise in the building industry.

Ultimately, engaging a diverse group of stakeholders is essential for achieving sustainable outcomes in circular economy projects. Stakeholders such as investors, regulators, suppliers, and local communities each have their own interests, whether related to profitability, environmental impact, or social responsibility. By using strategies like early involvement, transparency, and collaborative decision-making, these stakeholders can align their goals and work together more effectively. This collaboration not only drives innovation but also helps to create more sustainable, resilient, and successful project outcomes (Adebayo et al. 2024a).

3.3 Factors that influence material reusability

Key factors can be found in literature that influence the reusability of materials in construction.

Table 2 present an overview of key factors and subfactors influencing material reusability as identified in the literature including a general classification of the factors. The factors encompass considerations from standardization and quality to disassembly potential, logistics, risk, environmental evaluations, economic, policy and stakeholders, illustrating the multifaceted nature of circular renovation projects. These factors are categorized into six classifications: Technical, Functional, Environmental, Financial, Organizational, and Stakeholder. The table also shows how each factor is measured in the literature, either quantitative or qualitative, and includes relevant sources

Table 2: Factors influencing material reusability in Literature

Classification	**Factor**	**Subfactor**	**Measurement**	**Source**
Technical	Standardization	Standard materials	Quantitative	(Charlotte et al. 2022; Condotta et al. 2021; Ottosen et al. 2021; Matrai 2019)
	Standardization	Component uniqueness	Quantitative	(Coenen et al. 2021)
	Standardization	Design phase standardization	Qualitative	(Hradil et al. 2019; Da Silva 2023)
	Quality	Material condition	Quantitative	(Devènes et al. 2024; Bellini et al. 2024)
	Quality	Life expectancy	Quantitative	(Bellini et al. 2024)
	Quality	Material inspections	Quantitative	(Bellini et al. 2024)
	Quality	Product documentation	Quantitative	(Bellini et al. 2024)
	Quality	Technical requirements (structural)	Quantitative	(Bellini et al. 2024; Matrai 2019)

Classification	Factor	Subfactor	Measurement	Source
Functional	Disassembly Potential	Component interfaces and connections	Quantitative	(Coenen et al. 2021)
	Disassembly Potential	Design for disassembly	Qualitative	(Bellini et al. 2024)
	Disassembly Potential	Ease of deconstruction	Quantitative	(Bellini et al. 2024)
	Logistics and Storage	Transportability	Quantitative	(Coenen et al. 2021)
	Logistics and Storage	Storage capacity and location	Quantitative	(Almeida et al. 2022; Bellini et al. 2024)
	Logistics and Storage	Availability and scheduling of materials	Quantitative	(Bellini et al. 2024)
	Logistics and Storage	Storage duration and preservation	Quantitative	(Bellini et al. 2024)
	Logistics and Storage	Infrastructure	Qualitative	(Coenen et al. 2021)
	Logistics and Storage	Sorting and storage facilities	Qualitative	(Bellini et al. 2024)
	Logistics and Storage	Transportation logistics	Quantitative	(Bellini et al. 2024)
	Risk Evaluation	Economic risks	Qualitative	(Bellini et al. 2024)
	Risk Evaluation	Technical risks	Qualitative	(Bellini et al. 2024)
	Risk Evaluation	Uncertainty due to limited data	Qualitative	(Bellini et al. 2024)
	Risk Evaluation	Risk management	Qualitative	(Bellini et al. 2024)
Environmental	Environmental Evaluation	Carbon-saving potential	Quantitative	(Bellini et al. 2024)
	Environmental Evaluation	Hazardous material identification	Qualitative	(Bellini et al. 2024)
	Environmental Evaluation	Energy consumption	Quantitative	(Bellini et al. 2024)
	Environmental Evaluation	Recyclability of materials	Qualitative	(Bellini et al. 2024)
Financial	Economic	Landfill and incineration taxes	Quantitative	(Gonzales et al. 2022)
	Economic	Market creation for reusable materials	Qualitative	(Banias et al. 2022)
	Economic	Financial benefits	Quantitative	(Nußholz et al. 2020; Schützenhofer et al. 2022)
	Economic	Cost evaluation (logistics, quality, risk)	Quantitative	(Bellini et al. 2024)

Classification	Factor	Subfactor	Measurement	Source
Organizational	Policy	Pre-demolition audits	Qualitative	(Condotta et al. 2021; Spišáková et al. 2022)
	Policy	Mandatory regulations for material reuse	Qualitative	(Condotta et al. 2021)
	Policy	Knowledge sharing platforms	Qualitative	(Christensen et al. 2022)
	Policy	Stakeholder awareness and collaboration	Qualitative	(Christensen et al. 2022; Matrai 2019; Adebayo et al. 2024b)
	Organization	Reuse in Design Process	Qualitative	(Rakhshan et al. 2020)
	Organization	Reuse in Contract	Qualitative	(Rakhshan et al. 2020)
	Organization	Components management coordinator	Qualitative	(Rakhshan et al. 2020)
	Organization	Experience with reused materials	Qualitative	(Tingley et al. 2017; Rakhshan et al. 2020)
	Stakeholder	Early engagement	Qualitative	(Heuvel 2024; Adebayo et al. 2024a)
	Stakeholder	Visual appearance concern of architects and contractors	Qualitative	(Rakhshan et al. 2020)
	Stakeholder	Collaboration	Qualitative	(Bellini et al. 2024; Adebayo et al. 2024b; Adebayo et al. 2024a)
	Stakeholder	Willingness to compromise	Qualitative	(Matrai 2019)
	Stakeholder	Transparent communication	Qualitative	(Adebayo et al. 2024b; Adebayo et al. 2024a)
	Stakeholder	Information exchange	Qualitative	(Bellini et al. 2024)
	Stakeholder	Risk-sharing	Qualitative	(Matrai 2019; Rakhshan et al. 2020)
	Stakeholder	Trust	Qualitative	(Matrai 2019)
	Stakeholder	Reputation	Qualitative	(Remmerden et al. 2025)
	Stakeholder	Public awareness of reuse	Qualitative	(Rakhshan et al. 2020)
	Stakeholder	Willingness to reuse	Qualitative	(Rakhshan et al. 2020)

3.3.1 Technical

Standardization

The need for standardization in the reuse of construction materials is frequently highlighted in the literature. A lack of consistent standards and technical specifications for reusable materials and lack of testing requirements hinders the widespread adoption of reusing construction materials (Charlotte et al. 2022; Condotta et al. 2021). Studies, such as Ottosen et al. (2021), suggest that material certification and stakeholder involvement in creating standards are key to improving reuse practices. Standardization should be integrated early in the project, ideally during the design phase (Hradil et al. 2019; Da Silva 2023), so that in the future the standardized materials can be reused. However, in cases like the renovation of the Amsterdam Quay Walls, this consideration of standardization is not applicable, as the focus is on reusing existing materials from the historical quay walls and bridges that were not originally standardized.

The reuse of construction components is influenced by their level of standardization, as standardized elements are more likely to be interchangeable and meet reuse demands. Logically, components with higher uniqueness are less likely to fit new locations, reducing potential reusability (Coenen et al. 2021).

Quality

The quality or condition of the existing material components is a key factor to the reusability of materials. Since construction materials evolve through time and climate influences, this can lead to damages and detrimental anomalies of load-bearing components. This influences the durability, serviceability, and safety of the material (Devènes et al. 2024) and therefore also its reusability potential. When it comes to assessing the reusability potential, the quality of the materials and the remaining life expectancy prior to reuse of the materials should be considered. An initial estimate of the state of the construction products/materials can be made based on a visual inspection, but to have a complete assessment of the quality of materials, it is recommended to consult the as-built documentation for the existing building, a record of maintenance interventions (since preventive maintenance can extend the lives of construction products), and the product documentation (Bellini et al. 2024). The condition of material components are most commonly assessed by doing a visual inspection, but other methods such as sensor measurements and 3D-scanning tools are also emerging (Devènes et al. 2024).

Reclaimed materials must also meet technical requirements, such as structural performance, fire safety, sound isolation, and thermal conductivity, depending on their intended function.

This may involve reviewing technical documentation, such as datasheets, logbooks, or CE markings, and conducting laboratory tests to verify mechanical and chemical performance. As knowledge about reusable materials grows, creating an open-access database can streamline future assessments by reducing the need for repetitive analyses (Bellini et al. 2024).

3.3.2 Functional

Disassembly Potential

This evaluation assesses if materials are composite or can be disassembled in a sensible way without compromising the quality of material. Reusing construction materials may be challenging due to their lack of design for disassembly, therefore the disassembly potential is taken into account when looking for reusable materials (Bellini et al. 2024). A component is considered to have a higher reusability potential if it is easily disassembled and transportable over the available infrastructure and has a standard design. Disassembly potential, particularly for bridges, largely depends on the internal connections between components. Identifying interfaces and the types of connections used is essential for determining ease of deconstruction. Components designed with fewer and simpler connections have higher disassembly potential, facilitating reuse easier (Coenen et al. 2021).

Logistics and Storage

The logistics related to deconstruction are also an important factor including sawing, storage, and transport capacities (Devènes et al. 2024). An efficient reuse process of materials requires careful consideration of availability of the product, when the product is needed, storage duration, and storage location. Logistics and storage issues can hinder the reusability process, impacting quality, cost, and risk of a project. Therefore, proper planning regarding knowing when materials are available and when they will be needed in the project is required for storage and logistics, and this often leads to extra project costs (Bellini et al. 2024). Adequate infrastructure, such as sorting, storage, and transportation facilities, and advancements in deconstruction methods are crucial. Almeida et al. (2022) highlight the need for designated storage sites for reusable materials. Logistics between demolition and new construction sites are also essential for material flow.

Transportability is a big factor when it comes to material logistics, since if a material cannot be transported within applicable rules and legislation, it cannot be reused in another location. Therefore, transportability is regarded as a precondition for reusability. Whether a component can be transported after its disassembly depends primarily on its dimensions and weight, with dimensions often posing greater limitations. The surrounding infrastructure (e.g., roads, rail, waterways) must be assessed to determine viable transport options (Coenen et al. 2021). Schützenhofer et al. (2022) and Cai et al. (2019) advocate for advancing deconstruction technologies, while others suggest that materials can be reused on-site, avoiding unnecessary transportation (Etienne et al. 2022). These improvements in logistics and storage support better material management and reuse efficiency.

Additionally, Bellini et al. (2024) highlights that there is a need for consideration about where to use the reclaimed materials in the new project. Evaluating the location of a reclaimed product in the new project requires continuous interaction and collaboration between project stakeholders, and it is necessary to collect documentation and information about the reclaimed products. However, a preliminary plan for the reclaimed materials in the project is important for smooth logistics and storage.

Risk Evaluation

Evaluating and quantifying the risks associated with reusing construction products is crucial, as material reuse requires a shift toward innovative thinking. The reuse process involves several types of risks: economic risks related to extended planning and logistics timelines, technical risks concerning product performance and life expectancy, and an initial level of uncertainty due to limited information and data. In circular projects, it is therefore important to plan the contingency accordingly due to possible risks involved. Additionally, risk management should clearly define, from the initial phase of the reuse process, who is responsible for managing and mitigating risks associated with reuse; this would in many cases be the contractor (Bellini et al. 2024).

3.3.3 Environmental Evaluation

Environmental evaluation focuses on measuring the carbon-saving potential of reusing reclaimed construction products compared to using new ones. The carbon footprint of materials is influenced by factors such as energy consumption during production, transportation, logistics, and recyclability. While reuse prevents the need for new production and reduces carbon footprints, project participants highlighted challenges in accurately calculating these savings due to uncertainty in quantifying the environmental benefits of specific reclaimed products. Additionally, identifying and addressing hazardous materials was also part of the environmental evaluation process (Bellini et al. 2024).

3.3.4 Economic

The economic factors promoting material reuse include implementing landfill and incineration taxes, which encourage stakeholders to seek alternative solutions (Gonzales et al. 2022). The rising costs of landfilling and waste disposal act as financial incentives for reuse, as companies seek to avoid additional fees. However, these drivers vary by region, as lower landfill costs in certain areas can discourage reuse in favor of cheaper disposal methods (Rakhshan et al. 2020). Additionally, creating markets for reusable materials can foster competition and provide incentives (Banias et al. 2022). The potential cost savings from using recovered building components further promote reuse, as lower material costs can contribute to overall project savings. An attractive pricing strategy for reused components can stimulate demand, fostering the growth of a secondary market and increasing revenue from the resale of salvaged materials. For instance, reusing structural elements such as steel sections reduces the need for purchasing new materials, making reuse a financially viable alternative (Rakhshan et al. 2020).

Furthermore, studies are needed to compare the financial benefits of sustainable practices versus traditional ones to demonstrate the economic advantages of material reuse (Nußholz et al. 2020; Schützenhofer et al. 2022). Cost evaluation plays a critical role in determining which products can be reused and how. This assessment is influenced by multiple factors, including logistics, quality and condition of the product, risk-related considerations, and opportunities for reuse (Bellini et al. 2024).

3.3.5 Organizational

Policy

The importance of regulations in promoting material reuse is emphasized, with pre-demolition audits being a key factor. Although existing protocols are beneficial, they are not mandatory in all countries (Condotta et al. 2021; Spišáková et al. 2022), and should be implemented as part of every construction project. Pre-demolition audits can significantly improve sustainability by helping stakeholders make better material choices. Additionally, increasing awareness and creating platforms for knowledge sharing can enhance stakeholder motivation and foster stronger collaboration across organizations (Christensen et al. 2022).

Organization

Incorporating reuse into the design process of new projects is a crucial method for increasing reuse rates. Studies suggest that contractual requirements explicitly stating reuse goals can further facilitate this process (Rakhshan et al. 2020). Also, the presence of a reclaimed components management coordinator and maintaining an early list of structural components available for reuse are also recommended to support adoption of reusable components (Rakhshan et al. 2020). Furthermore, experience and knowledge in working with reused materials, along with proper separation and handling techniques, are essential for improving the feasibility and desirability of reused components in construction projects (Tingley et al. 2017; Rakhshan et al. 2020).

Stakeholders

Effective stakeholder engagement plays a crucial role in enhancing the reusability potential of materials in projects. Early engagement, as emphasized by Heuvel (2024), allows for better alignment of stakeholder goals and reduces resistance, fostering a more cooperative environment. However, social barriers, such as negative perceptions of reused materials and reluctance of stakeholders due to perceived risks, can significantly hinder material reuse (Rakhshan et al. 2020). For instance, concerns regarding the visual appearance and quality of reclaimed materials often lead architects and contractors to prefer new materials over reused ones, despite potential sustainability benefits. Additionally, risk aversion, liability concerns, and lack of trust in suppliers further discourage reuse adoption (Rakhshan et al. 2020).

Collaboration among stakeholders, such as architects, contractors, and consultants, is key to addressing challenges related to material availability, quality, and non-standardization (Bellini et al. 2024). Transparent communication and collaborative decision-making, as highlighted by Adebayo et al. (2024b), enable stakeholders to share information and make joint decisions, ensuring that diverse interests are considered. Moreover, client motivation plays a decisive role. If clients prioritize reuse, resistance from designers and contractors can be overcome, while a lack of client support significantly reduces the chances of integrating recovered materials into projects. Additionally, the willingness to compromise, along with risk-sharing and the provision of additional resources, helps overcome institutional and contractual barriers that often hinder material reuse (Matrai 2019).

Reputation is an important factor in the renovation, influencing both decision-making and the feasibility of reusability, and it is also one of the factors considered in the Amsterdam's quay walls infrastructure maintenance model by Remmerden et al. (2025). Media coverage, political attention, and environmental perception can impact project approval and execution. Negative attention may lead to increased accountability and delays, while a positive reputation can facilitate smoother progress (Remmerden et al. 2025). Public awareness and growing environmental concerns among society play a significant role in promoting reuse (Rakhshan et al. 2020). The recognition of reuse in public discourse can help shift stakeholder perceptions and increase adoption rates. Lastly, willingness to integrate reusable components of the stakeholders (engineers, contractors, designers and client), as well as good relationships among these stakeholders and trust are reported to help overcome challenges and promote reusability in construction projects (Rakhshan et al. 2020).

3.4 QCA methodology and ML

Qualitative Comparative Analysis (QCA) is a widely used research methodology for systematically examining the similarities and differences between a set of comparable cases to identify the structural conditions that lead to an outcome (Ahuja et al. 2017). One of the ways to employ QCA in research is by integrating Machine Learning (ML) techniques. Several studies have combined QCA with ML to achieve significant insights.

3.4.1 Applications of ML in QCA Studies

Mu et al. (2025) employed a traditional logistic regression analysis using the Adaboost iterative algorithm to understand the influence of the built environment on the well-being of older adults. This study analyzed multiple factors to investigate the impact of the built environment on physical activity levels. Additionally, correlation analysis was conducted to deduce related factors.

Recent research demonstrates that nonlinear ML techniques, such as Random Forest (RF), Gradient Boosting Decision Tree (GBDT), and XGBoost, can effectively explore nonlinear effects. These nonlinear models provide significantly higher prediction accuracy compared to traditional linear regression models and are capable of capturing complex relationships (Liu et al. 2025).

3.4.2 ML Applications in Construction and Demolition Waste Reusability

Artificial intelligence is emerging in the construction industry through ML and computer vision techniques, enabling the prediction of the reusability of construction and demolition waste, including structural components (Byers et al. 2024).

Akanbi et al. (2020) highlights the application of deep learning models to establish meaningful relationships between building characteristics (e.g., archetypes, usage, gross floor area, number of floors, and volume) and material outcomes (recyclable, reusable, and landfill materials). These models achieved high prediction accuracy (average R-squared of 97%) and provided valuable insights into variable importance, using over 2000 demolition records. This illustrates the potential of ML techniques in uncovering structural conditions relevant to reusability potential in the built environment.

Similarly, Rakhshan et al. (2021) developed a probabilistic model using ML techniques (e.g., Random Forest, K-Nearest Neighbours, Gaussian Process, and Support Vector Machine) to predict the reuse potential of structural elements. The Random Forest model produced the most reliable predictions. Data was gathered through an online questionnaire completed by over 90 experts to assess barriers to reuse and develop an easy-to-understand tool for evaluating reusability. Findings emphasized that design-related factors, particularly the compatibility of recovered components with new building designs, significantly influence reuse potential.

3.4.3 Application in Amsterdam's Quay Wall and Bridge Projects

In the context of this research on Amsterdam's quay wall and bridge projects, similar ML techniques can be employed to assess reusability potential. The focus will be on the dependent factor (reusability potential) and a set of independent factors, including both data- and stakeholder-related variables. By collecting historical data and project-specific information from Logiquay, ML can uncover patterns and correlations among these factors, providing insights into which elements most significantly influence reusability potential.

When cases and data necessary for analysis are limited, the use of generative data may be explored. However, due to the recent nature of the technology, comparable research utilizing QCA methods with generated data in the field of the built environment is currently unavailable as a reference for this research.

3.5 Research Gaps Identified

The literature review reveals several critical gaps in understanding and advancing the reusability potential of construction materials, particularly in the context of sustainable renovation of urban infrastructure such as Amsterdam's quay walls and bridges. These gaps can be summarized as follows:

- A strong collaboration among the project stakeholders (architects, project owners and contractors) and early involvement of architects and consultants in projects is critical in projects involving reusability of materials (Bellini et al. 2024). While Heuvel (2024) provides a thorough analysis of stakeholder roles in the renovation of Amsterdam's infrastructure, it does not address the reusability aspect in the context of circular renovation. A gap on how contractors and engineering firms contribute to assessing and implementing material reusability is identified. There is a need to explore how stakeholders interact and share data relevant to reusability assessments. This gap will be addressed in this research, which will examine stakeholder interactions, data exchange, and the role of contractors and engineering firms in optimizing reusability potential for circular renovations.

- The literature highlights several factors that influence the reusability potential of construction materials, including quality, disassembly potential, logistics, risk evaluation, and economic and environmental assessments. While these factors have been explored in existing studies, there is a notable gap in understanding the relative impact of these factors, particularly in specific contexts like the renovation of Amsterdam's quay walls and bridges. Existing quantitative researches have predominantly focused on the technical aspects of material reuse, such as structural components and waste records (Byers et al. 2024), but less attention has been paid to how much stakeholder engagement, communication, and data sharing affect the reusability process. Stakeholders' involvement and decision-making in the early stages of projects, as well as the complexity of coordinating the information, are crucial in overcoming the challenges of material reuse (Bellini et al. 2024; Adebayo et al. 2024a). This gap in the literature shows a need for further research into how different factors, including stakeholder roles and interactions, influence the reusability potential of materials. This research will address this gap by exploring these factors through interviews with key stakeholders involved in the renovation projects. Additionally, a machine learning model will be employed to quantitatively assess the relative impact of the chosen factors that will be analyzed, helping us better understand how each element contributes to the overall reusability potential. This approach will provide insights into the most significant factors, offering valuable information for future circular renovation projects.

- While pre-demolition audits provide significant benefits in waste reduction (Rašković et al. 2020), worker safety (Wahlström et al. 2019), and cost efficiency (Da Silva 2023), there remains a critical gap in understanding how to effectively structure and use reusability data for future projects. Current guidelines, while informative, often lack practical application strategies for integrating data in ways that enhance circular renovation efforts systematically. This study addresses this gap by analyzing the types of information gathered in audits and identifying methods to structure reusability potential data, which will support future reuse, and decision-making in large-scale urban renovation projects.

The reviewed literature indicates that the reusability potential of construction materials is shaped by a complex interplay of technical, functional, environmental, economic, and organizational factors. However, most studies emphasize technical dimensions, while the roles of stakeholder engagement, data exchange, and collaborative processes remain insufficiently explored.

This study seeks to address these identified gaps through an approach that integrates qualitative insights from stakeholder interviews. The factors identified in the literature review serve as a foundation for the interviews to examine which factors interviewees perceive as most important. This is done particularly within the context of the sustainable renovation of Amsterdam's quay walls and bridges, alongside quantitative analysis using machine learning techniques. By doing so, the research aims to determine the relative importance of various factors affecting reusability potential and to contribute practical knowledge for enhancing sustainable renovation strategies.

4 Stakeholder Insights

In this chapter, we explore the insights gathered from stakeholders involved in the renovation of Amsterdam's bridges and quay walls, focusing on their roles, contributions, and perspectives regarding the assessment of material reusability. The findings are based on semi-structured interviews conducted with key individuals from various sectors, including contractors, engineers, city experts directly engaged in the renovation projects.

Through these interviews, we address two main aspects of the research: the types of data and information collected in pre-deconstruction audits and the influence of stakeholders on the reusability assessment process. These aspects are aligned with sub-questions 1 of the research. Additionally the interviews will identify the technical and stakeholder related factors that are most important to stakeholders, which will answer sub-question 2.

This chapter presents the responses from the stakeholders, highlighting their perspectives on the data, and human factors influencing material reuse, as well as suggestions for improving the overall assessment process. By examining these insights, we can better understand the dynamics of stakeholder involvement and its impact on the success of reusability assessments in urban renovation projects. The interview guide used to structure the conversations is provided in Appendix A.1. To analyze the interviews, a thematic coding process was used to identify and organize recurring patterns and insights across stakeholder responses. The resulting themes were systematically labeled and linked to the relevant interviewees and content. This coding structure is presented in Appendix A.3, while Appendix A.4 includes the full interview transcript notes.

4.1 Interviewee Information

The table below provides a summary of the interviewees, their roles, and the companies they represent.

Interviewee	Role	Company
Interviewee 1	Project Lead	Amsterdam Municipality
Interviewee 2	Project Lead	Count & Cooper and Beens (Contractor)
Interviewee 3	Contract Manager	Antea Group (Engineering Firm)
Interviewee 4	Project Lead & Technical Manager	Witteveen & Bos (Engineering Firm)
Interviewee 5	Project Controls Manager	Amsterdam Municipality

Table 3: Interviewees, Roles, and Companies

4.2 Data and Information

This subsection focuses on the insights gathered from stakeholders regarding the types of data and information used in the assessment of material reusability during the pre-deconstruction audit phase. The interviews shed light on the most commonly collected data, challenges faced in obtaining certain types of information, and how this data is analyzed, shared, and utilized by stakeholders.

4.2.1 Types of Data Collected During Pre-Deconstruction Audits

Stakeholders emphasized that a variety of data types are collected before deconstruction begins. These include:

- Investigations on the remaining lifetime of materials.
- Quality assessments of structural elements.
- Specific investigations on piles to assess their condition and potential for reuse, particularly to determine the condition of wooden elements, which are often found to be of poor quality and unsuitable for reuse.
- Conditioning investigations, including soil tests and historical data.
- Design drawings of the existing structure.
- Condition reports on nearby trees

While a Building Information Model (BIM) would be highly beneficial in centralizing and visualizing this data, stakeholders noted that such models are usually not available for older infrastructure. Instead, teams often reconstruct information from old design drawings, which can be time-consuming and potentially incomplete.

4.2.2 Timing and Purpose of Data Collection

The timing of data collection varies depending on the type of component being assessed:

- For structural construction components, data should ideally be gathered during fase 3 (conditionering), prior to the finalization of the design (fase 4), to prevent costly surprises and allow for informed decisions.
- For components located in public space (such as pavement stones) data collection can occur slightly later in the design process.

This distinction reflects the different levels of design integration and technical complexity associated with various material types.

4.2.3 Factors Influencing Reusability Potential

A number of technical and policy-related factors were identified as influencing the potential for reuse:

- **Design Flexibility:** Projects that are defined as renovation (rather than new-build) from the start have greater potential for incorporating reused components. This decision is made early in the process through a Multi-Criteria Analysis, which currently does not formally include reuse potential as a criterion.
- **Requirements in Design Stage:** The earlier reuse considerations are integrated into the design requirements, the more feasible reuse becomes.
- **Quality Check:** The quality of materials is a decisive factor for the remaining lifespan of the potentially reusable components, and thorough assessments and tests are essential.
- **Material Homogeneity:** Homogeneous materials such as cap stones (dekstenen) and paving stones are easier to reuse compared to materials with complex assembly (e.g., masonry with mortar joints).
- **Aesthetic Considerations:** New projects must meet strict aesthetic guidelines set by the city municipality, which can limit the use of visibly aged or inconsistent materials. Designers are bounded by these guidelines.
- **Policy Requirements:** Stakeholders mostly follow the policy and contract requirements set by the municipality for the projects. Therefore, a mention or requirement for sustainability or reuse is crucial for the actual reuse potential of projects. Since 2024, the municipality has introduced reuse requirements, which stakeholders view as a positive step toward more sustainable renovation practices.

Commonly reused materials include cap stones (dekstenen), street bricks, balusters, and sheet piles. Materials in poorer condition such as wood piles are often redirected to alternative uses like art installations or furniture. Stakeholders also noted that sheet piles are also commonly reused in other projects when available in good condition.

4.2.4 Barriers to Reuse and Information Challenges

Despite growing interest in reuse, several barriers remain:

- **Limited Opportunities for Reuse:** The technical and design requirements of each project, especially in densely populated or canal-side areas, limit what can feasibly be reused. Many project scopes are locked in early and categorized as new-build or demolition, leaving limited room for reuse exploration.

- **Strict Design Guidelines:** The aesthetic and functional demands of the city limit the flexibility of integrating reused materials.

- **Uncertainty About Quality:** Without standardized procedures or records, assessing the true quality and remaining lifespan of old materials can be difficult.

- **Higher Costs:** In some cases, reuse may incur additional costs for testing and adaptation.

- **Design Rules and Maintenance:** Design codes and long-term maintenance requirements may make reuse less attractive or feasible, leading to trade-offs in decision-making.

- **Fragmented Data Management:** Currently, data is shared via email, SharePoint, or PDF reports, with limited centralization. Although BIM is being introduced in the projects (especially using 3D models in Revit), BIM models are often not shared across contractors or project teams.

In terms of data management, the lack of integrated digital systems (such as BIM) was mentioned as a significant gap. Data is often scattered or embedded in outdated formats, making it hard to share efficiently across teams or projects. This complicates collaborative decision-making and reduces the overall efficiency of reuse assessments. Stakeholders also mentioned the importance of developing a live database that links supply and demand for reusable materials in the city. Some materials are stored in municipal depots and can be requested for reuse, but this system is not yet fully integrated with project planning workflows.

Ultimately, interviewees expressed a vision in which reuse becomes the default and deviation from it must be justified. However, achieving this will require significant changes to the way data is collected, analyzed, and shared, particularly during the early project phases.

4.3 Stakeholder-Related Insights

This subsection focuses on the role of various stakeholders in shaping the reusability assessment process. Interviews reveal how diverse stakeholders,ranging from municipal departments to contractors and designers, impact both data collection and decision-making. The insights also highlight misalignment in stakeholder priorities, how these affect reusability assessments, and the potential for improved collaboration in future circular renovation projects.

4.3.1 Identification of Key Stakeholders

Several key stakeholders were identified as central to the reusability assessment process. These include:

- **Municipality and government bodies**, who act as the main decision-makers by setting policy, technical requirements, and reusability goals. This includes the program management, V&OR (Verkeer en Openbare Ruimte), Traffic and Public Space.
- **Contractors** and **engineering firms**, who execute the work and often express support for reuse when feasible.
- **Maintenance teams**, responsible for long-term upkeep (often 100 years), who are particularly sensitive to reusability due to limited budgets.
- **Designers**, especially those focused on aesthetics, who may be more flexible but are constrained by the city's strict visual guidelines.
- **Community stakeholders**, such as nearby residents or boat tour operators, who are impacted by project disturbance.

4.3.2 Stakeholder Interests and Conflicts

The interviews revealed varying and sometimes conflicting interests among stakeholders as illustrated in the stakeholder map (Figure 3):

- **Maintenance teams** prioritize low-maintenance solutions due to budget constraints, often viewing reused materials as riskier due to higher future maintenance needs.
- **Contractors and engineers** generally favor reuse when it is feasible and economically viable, butcontractors often prefer new materials for reasons of speed and ease.
- **Designers** tend to be more open to reuse but are limited by strict aesthetic and heritage requirements from the municipality.
- **Municipal policy** recently includes sustainable requirements, since 2024 includes reuse promotion, yet it also enforces lifetime, quality, and aesthetic standards that may limit reusability in practice. Reuse is not a strict requirement, more so sustainability is promoted.

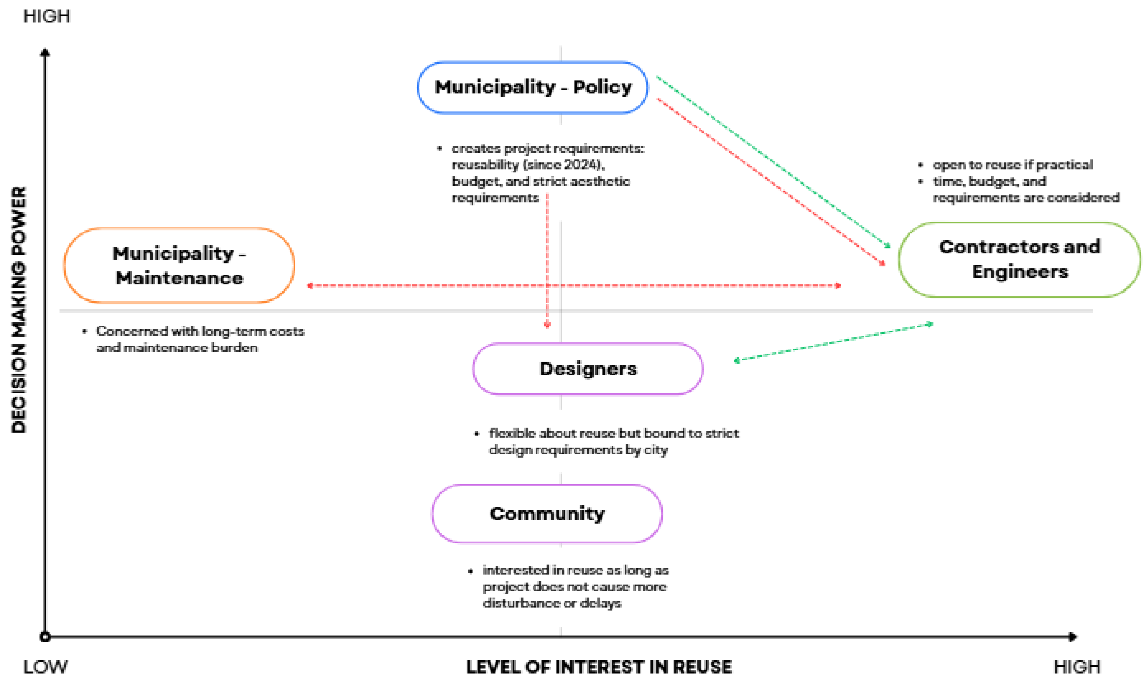

Figure 3: Stakeholder Influence and Interests in Reusability

These differences often lead to trade-offs in decision-making, where reuse goals may conflict with aesthetic or budgetary considerations.

4.3.3 Decision-Making Dynamics

Decision-making authority resides primarily within the municipality, which consists of multiple teams, each with its own focus. For instance:

- The **engineering team** makes technical assessments.
- The **maintenance department** evaluates long-term durability and cost implications.
- **Policy-makers and political leaders** shape the regulatory environment that either facilitates or hinders reuse.

The decentralized nature of decision-making within the municipality means that coordination and alignment of priorities can be challenging.

The decision-making process involves multiple phases:

- **Phase 3 (Conditioning)** includes a multi-criteria analysis (MCA) to determine project type (e.g., renovation with reuse, demolition, or new build) based on criteria such as technical feasibility, tree preservation, and spatial impact. Notably, reusability is not yet formally part of this MCA. Baed on the result of this MCA, Amsterdam creates a BVM (Besluit veiligheidsmaatregel) which states whether the project is a new build, demolition or renovation.

- **Phase 4 (Design)** Based on the BVM decision of project type, the design is made.
- **Phase 3 (Execution)** where implementation occurs.

Engineering firms and contractors are generally involved after the project type decision is made and thus have limited influence on early strategic choices related to reuse.

4.3.4 Stakeholder Influence on Reuse Potential

Stakeholders impact reusability potential in several ways:

- Early contractor involvement during the engineering phase can improve the feasibility of reuse by aligning technical and practical considerations.
- City-imposed execution methods, such as restrictions on vibrations in central areas, limit the types of materials or techniques that can be applied.
- Disturbance to the community (e.g., residents, tourists) must be minimized, influencing whether reuse is pursued, especially if it increases construction time or logistical complexity.
- Budget flexibility and proximity to city center both affect which reuse options are considered viable.
- Certain materials are location- or method-specific and cannot be reused in contexts with incompatible installation requirements.

4.3.5 Information Exchange and Future Improvements

Several suggestions were made to improve stakeholder collaboration and data sharing:

- A **shared material bank or database** is envisioned, where reusable materials from one project can be synced and shared with other ongoing projects, though this currently happens only within the same contractor.
- The use of **BIM models**, particularly 3D Revit models, can support more structured reuse assessments. These models can define phases of work and promote better planning across stakeholders.

- Uploading 3D models to the **AEP database** is proposed as a future improvement to enable cross-project collaboration.

4.3.6 Machine Learning: Future Uses

Stakeholders identified several opportunities for leveraging machine learning models to support the circular renovation of bridges and quay walls in Amsterdam:

- The ML model could serve as a city-wide tool to assess and predict reusability potential across all projects, creating a unified and scalable method for reuse assessment ("areaal benadering").
- A centralized ML-based database could match supply and demand for reusable materials between projects. This would prevent long-term storage needs, reduce costs, and support business case development for reuse.
- Insights such as production year or construction period of a structure were highlighted as important indicators of reusability. Older structures are less likely to be reusable due to degradation but could still be repurposed (e.g., art, street furniture, or road foundations).
- ML models could include additional predictive factors such as distance from houses to the quay wall, which affects construction disturbance and hence reuse feasibility in urban environments.
- Stakeholders emphasized that a predictive model should be developed with an eye on collaborative use, allowing data sharing between contractors and city departments for future renovation planning.

4.4 Answering research question 1

Reusability potential is shaped by both technical data and stakeholder dynamics. Key technical inputs include historical drawings, visual inspections, damage reports, and material testing. These form the basis for evaluating the physical condition of elements prior to potential reuse. However, reusability is not determined by technical data alone.

Stakeholders influence the reusability potential in multiple ways: the municipality defines project scope and sustainability goals; engineering firms conduct technical evaluations; and contractors assess practical feasibility. Political decisions, aesthetic policies, and citizen perspectives further shape what is considered reusable. Fragmented responsibilities and limited data standardization pose additional challenges. Improving reuse practices requires better coordination between stakeholders, clearer assessment criteria, and the effective use of digital tools like BIM and shared data environments.

Based on insights from both the literature review and stakeholder interviews, this sub-question has been addressed: What information and data are available for assessing reusability potential and preparing the pre-deconstruction audit, and how do different stakeholders influence the assessment of reusability potential?

4.5 Most important factors to stakeholders for reusability

Building on the insights gathered regarding data, information and stakeholder dynamics, this section identifies the factors that stakeholders consider most important to reusability in projects. Through the interviews, stakeholders ranked technical and non-technical factors.

This information is crucial for shaping the next phase of the research, where project data will be collected for the four identified factors and analyzed using machine learning. By aligning the selected factors with stakeholder priorities, the analysis aims to improve the predictive accuracy of reusability assessments and support more informed decision-making in circular renovation projects. At the end of each interview, participants completed a short questionnaire where they rated predefined technical, functional, and organizational factors on their importance for reusability (1–5 scale). To narrow the scope of this research and considering the limited choice of 4 factors for the machine learning model, the choice was made to exclude economic and environmental categories in the list of factors sent to the interviewees. Since this research focuses on technical and stakeholder related factors, the choice was made to only include the factors listed in categories technical, functional and organizational. Along with the form, the interviewees selected the four most critical factors for use in predictive models and could suggest any additional factors they felt were missing from the list and were also important. The complete results from all interviewees are presented in Appendix A.5.

4.5.1 Overview of Importance Scores by Factor Category

The responses revealed that technical and organizational factors were perceived as more important for reusability than functional factors. The average scores were as follows:

Factor Category	Average Importance Score
Technical Factors	3.73
Organizational Factors	3.53
Functional Factors	2.86

Table 4: Average importance scores by factor category

Among the technical factors, the most important to stakeholders were:

- **Material condition** (avg. score: 4.6): Stakeholders emphasized that damage, aging, and degradation critically influence the reusability of materials.
- **Design phase standardization** (avg. score: 4.0): Integrating standardization early during design was seen as key to enabling reuse in future projects.

- **Life expectancy** (avg. score: 4.0): Materials with longer usable life remaining were viewed as more viable for reuse.

Within the organizational factors, the highest-rated were:

- **Reuse in Design Process** (avg. score: 4.4): Embedding reuse considerations early in design was considered essential.
- **Willingness to reuse** (avg. score: 4.4): Stakeholders highlighted that a proactive attitude toward reuse among engineers, contractors, and clients is critical.
- **Reuse in Contract** (avg. score: 4.0): Including reuse objectives contractually helps institutionalize circular practices.

While functional aspects such as disassembly potential and logistics were acknowledged, they consistently scored lower across interviews. However, one functional factor, Ease of deconstruction (avg. score: 3.6), stood out slightly above others in this category.

4.5.2 Key Factors Identified

Based on both frequency of selection and average importance ratings, the following four factors were selected by stakeholders as the most critical for inclusion in the predictive model:

- **Reuse Policy**
  Formal reuse requirements in contracts or guidelines were seen as essential to enable circular practices.
- **Willingness to Reuse**
  Stakeholder openness and commitment to reuse during design and execution phases was considered crucial.
- **Material Quality and Testing**
  The combination of good material condition and proper testing was key for assessing reuse potential.
- **Early Engagement of Stakeholders**
  Involving key stakeholders early, including the community, helped identify reuse opportunities from the start.

4.5.3 Factor Rating Scale

These factors were not only highly ranked but also appeared consistently in interview narratives, indicating a strong alignment between perceived importance and real-world experience. To guide future predictive modeling, a structured rating scale from 0 to 4 for each factor was developed based on qualitative insights. The factor scale is shown on Figure 4. In this scale, the score for material quality and inspections is taken on average to get the score for material quality/testing.

Factor / Factor Rating	0	1	2	3	4
Reuse Policy	No mention of sustainability or reuse in policy or contract	Sustainability mentioned, but not enforced	sustainability required but reuse not enforced	Reuse required but with flexibility	Reuse requirement in contract or municipal guideline
Willingness to Reuse	Stakeholders explicitly resistant to reuse	Low interest; reuse seen as extra effort	Neutral or situational support	Generally supportive and open to reuse	All stakeholders actively encourage for and integrate reuse in design and execution process
Material Quality/ Condition	All materials are heavily damaged or severely deteriorated; not suitable for reuse.	Most materials are in poor condition and unusable without significant repair.	some components usable with repairs, condition varies.	Good condition with minor issues for some components	Materials are in good condition and suitable for reuse across multiple components
Material Testing	No testing or documentation	Visual inspection only	Basic testing done	Testing and documentation available	Full testing with focus on assessing reusability potential
Early Engagement	No early engagement; stakeholders only informed during or after execution	Engagement happened late; only limited stakeholders involved	Some early engagement; 1–2 key parties consulted	Early engagement of most stakeholders; input considered	Structured, proactive engagement of all key stakeholders (including community) from start

Figure 4: Assessment Criteria and Rating Scale for Key Factors Influencing Reusability

4.6 Answering research question 2

The analysis of stakeholder interviews and factor rankings revealed that both technical and organizational factors are considered most important for reusability. Specifically, four key factors were identified as critical for inclusion in predictive models: reuse policy, willingness to reuse, material quality and testing, and early engagement of stakeholders. These factors reflect stakeholder priorities and provide a clear foundation for the machine learning model.

With the identification of the four factors, we have the answer to research sub-question 2: Which factors are most important to stakeholders for reusability?

5 Key Factors and Machine Learning Analysis

In this section, we focus on the key factors influencing the assessment of reusability potential in the renovation of Amsterdam's bridges and quay walls. We collect data for these factors from historical records and reusability scans, along with insights gathered from stakeholder interviews. The objective is to train a machine learning model to predict reusability potential based on these factors.

The workflow for the machine learning model consists of five main steps: (1) data collection from PBK stakeholder interviews and Nebest technical inspections; (2) data preparation, including cleaning and handling missing values; (3) training multiple machine learning models such as Decision Trees, K-Nearest Neighbours, Support Vector Regression, Bayesian Ridge Regression, and Random Forest; (4) selecting the model with the best prediction accuracy based on R^2 score; and (5) validating the selected model and providing future recommendations for improving reusability assessments. This workflow is illustrated in Figure 5.

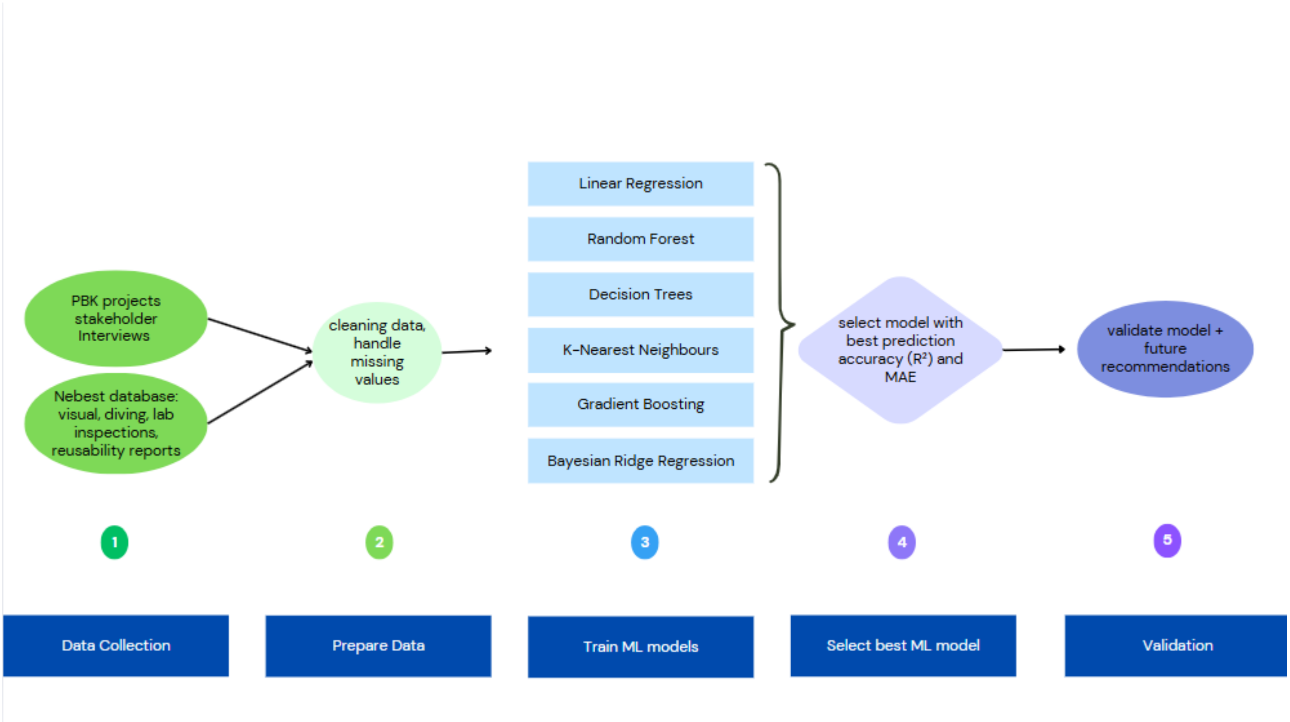

Figure 5: Machine Learning workflow

The resulting machine learning model takes as input four key factors (both technical and organizational) that were identified through the stakeholder interviews. These factors are fed into the trained model to generate a prediction of the reusability potential (in percentage) for a given project. This simplified functioning of the model is illustrated in Figure 6, showing how the input factors lead to the reusability potential prediction outcome.

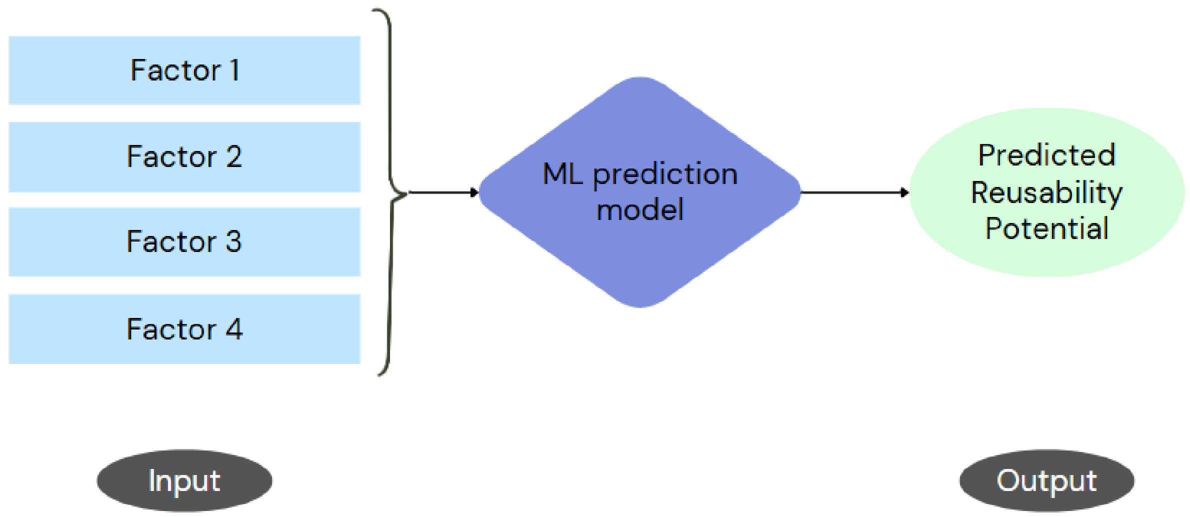

Figure 6: How the Machine Learning Models works

5.1 Data Collection and Key Factors

For the development of the machine learning model, the data was categorized into two primary types: technical data and stakeholder-related factors. Information regarding these factors was gathered through interviews with key stakeholders involved in the renovation process. The interviews aimed to identify the key factors that influence decisions regarding material reuse. These stakeholders were asked to rank various factors based on their importance in determining reusability potential, using a ranking form derived from a comprehensive literature review. Based on these rankings, four key factors were selected for the machine learning model. These chosen factors formed the basis of the predictive model, which aims to estimate the reusability potential for future projects.

A total of 20 completed and ongoing quay wall and bridge renovation projects in Amsterdam were included in the ML model, see Figure 7 (with completed projects displayed in green, ongoing projects displayed in blue, and planned projects displayed in red). Of these, 16 projects were used for training the machine learning model, while the remaining 4 were reserved for testing and validation purposes.

The data for these projects was collected through the following sources:

- **Stakeholder Interviews:** Insights were gathered from PBK-involved stakeholders, including engineers, contractors, and municipal authorities. These stakeholders provided

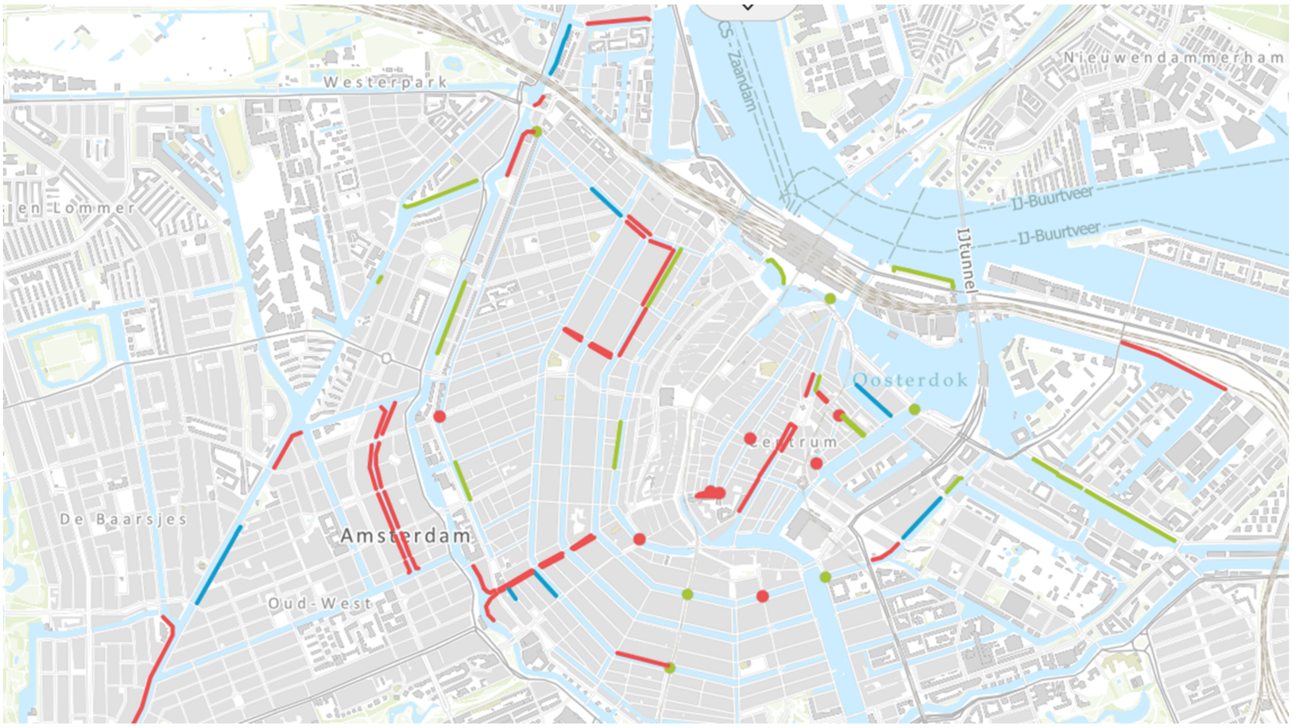

Figure 7: Amsterdam Bridges and Quay Walls Dashboard: projects

valuable input on the factors they perceive as critical when assessing reusability. Their insights helped in selecting the factors for the machine learning model. After selecting the 4 factors for the machine learning model, a form was sent to the interviewees to score the projects they worked on on the 4 factors (0 to 4) and the actual reused material percentage.

- **Nebest Database:** The Nebest database is an extensive repository of inspection data used for assessing the condition and reusability potential of materials in Amsterdam's bridge and quay wall projects. Thanks to our collaboration with Nebest, we gained access to their internal tool, which includes reusability scans of a couple bridges, and visual inspections, diving inspections, and lab test results from the remaining multiple bridge and quay wall projects. Nebest's internal tool provided detailed insights into the condition, availability, inspections, and potential for reuse of material components, helpful for evaluating the reusability of the different projects.

The collected data for 16 projects, which includes scores for the 4 factors and the actual reused material percentage, was used to train the machine learning models. To test the models, data of 4 projects were used by comparing the predicted reuse percentage to the actual reused percentage using metrics such as R^2 and Mean Absolute Error.

The combination of stakeholder insights and technical data from Nebest provided a well-rounded dataset that formed the foundation of the machine learning model.

5.2 Machine Learning Model Training and Testing

The objective is to train a machine learning model that predicts the reusability potential of materials based on the identified key factors. A total of 20 completed projects from the Amsterdam bridges and quay walls renovation are used for training and testing the model. The first 16 projects are used as the training set, and the remaining 4 projects are used as the test set.

5.2.1 Key Factors for Model Training

The machine learning model is trained using four key factors that are believed to influence reusability:

- **Reuse Policy**
- **Willingness to Reuse**
- **Material Quality and Testing**
- **Early Engagement of Stakeholders**

In the ML model, these factors are used as input variables to predict the reusability potential of materials.

5.2.2 Machine Learning Models and Their Functionality

Machine learning refers to the process of training algorithms to identify patterns within datasets and make predictions based on these learned relationships. Supervised learning, the approach used in this study, requires labeled data to train a model, which then makes predictions on new data (Brown 2021). To determine the best-performing model, several machine learning algorithms are tested in this research. These algorithms vary in complexity and approach, offering different strengths in terms of prediction accuracy, interpretability, and performance.

- **Linear Regression:** A standard Linear Regression model will be tested to evaluate whether a simpler, interpretable model can achieve comparable predictive performance. Linear Regression makes the assumption of a linear relationship between the input factors and the reusability potential and serves as a baseline for comparison to the other machine learning models (Kanade 2022).
- **Random Forest:** Random Forest is an ensemble learning technique that builds multiple decision trees, each tree in the forest is then trained on a random subset of the data.

The final prediction is made by averaging the predictions of all trees (for regression) or majority voting (for classification). This approach increases accuracy and reduces overfitting, making it well-suited for capturing complex, non-linear relationships between input factors and target variables (reusability potential) and making it able to handle large datasets with higher accuracy and robustness (Rakhshan et al. 2020; Rakhshan et al. 2021).

- **Decision Trees:** A Decision Tree is a simple, interpretable model that predicts outcomes by successively splitting the data based on feature values, forming a tree-like structure. Each decision point (node) corresponds to a feature test, leading to branches and eventually terminal nodes (leaves) with outcome values. that splits the dataset into subsets based on feature values, resulting in a tree-like structure. Each internal node represents a feature, each branch represents a decision rule, and each leaf node represents the output prediction. While Decision Trees are easy to visualize and interpret, they can be prone to overfitting when the tree grows too complex. Pruning techniques and ensemble methods such as Random Forest are often used to improve their performance (James et al. 2013).

- **K-Nearest Neighbors (KNN):** K-Nearest Neighbors (KNN) is a non-parametric model that makes predictions based on the majority class (for classification) or average (for regression) of the k nearest training samples to a given test sample. It is a simple, intuitive model that does not assume any underlying data distribution. KNN can work well for small datasets, but it becomes computationally expensive as the dataset grows because it requires calculating distances between all points and the results are highly sensitive to the choice of k and the distance metrics (Rakhshan et al. 2021; Murphy 2012).

- **Gradient Boosting:** Gradient Boosting is a machine learning technique that is commonly used for both regression and classification problems. It builds a predictive model in a sequential manner, where each new model attempts to correct the errors made by the previous ones by sequentially adding weak learners, such as usually shallow decision trees, that correct the errors of previous models. At each stage, the algorithm fits a new model to the residuals (errors) of the current ensemble using gradient descent to minimize the loss function. Its iterative nature allows the model to progressively improve performance, and also accuracy (Clark et al. 2025; Friedman 2001).

- **Bayesian Ridge Regression:** Bayesian Ridge Regression is a probabilistic model that applies Bayesian inference to linear regression. It assumes that the regression coefficients follow a Gaussian distribution and applies a prior to them. The model estimates both the coefficients and their uncertainties, providing a probabilistic framework for predictions.

Bayesian Ridge Regression is useful when dealing with multicollinearity or when a regularized approach is needed. It helps prevent overfitting by introducing a penalty for large coefficients (Murphy 2012).

5.2.3 Model Evaluation and Selection

Each model is trained using the 16 projects in the training set, and their prediction accuracy is evaluated using the R-squared (R^2) metric and the Mean Absolute Error (MAE). The R^2 score indicates how well the model explains the variance in reusability potential, with an R^2 score closer to 1 indicating better predictive performance. An R^2 score below 0 indicates an inaccurate model that performs worse than simply predicting the mean. The MSE measures the average absolute difference between the predicted and actual values, providing insight into the magnitude of prediction errors. A lower MAE corresponds to more accurate predictions.

After training all models, the one with the highest R^2 score and lowest MAE is selected as the final model. The performance of the selected model is validated by comparing its predictions with actual outcomes from the test set, assessing its accuracy, through the R^2 score.

Table 5 summarizes the performance metrics of all trained models.

Table 5: Performance of Machine Learning Models on Reusability Potential Prediction

Model	**R^2 Score**	**Mean Absolute Error (MAE)**
Linear Regression	0.576	15.838
Decision Trees	0.946	6.500
Random Forest	0.740	12.147
K-Nearest Neighbors (KNN)	0.796	9.167
Gradient Boosting	0.950	5.359
Bayesian Ridge Regression	0.803	11.807

Among the models evaluated, the Gradient Boosting model demonstrated the best overall performance, achieving the highest R^2 score of 0.950 and the lowest MAE of 5.359. This indicates that it explains about 95.0% of the variance in reusability potential within the training data and produces the smallest average prediction error compared to the other models. The Decision Tree model also performed well ($R^2 = 0.946$), though its slightly higher error suggests less consistent accuracy compared to Gradient Boosting. Simpler models such as Linear Regression had lower R^2 scores and higher errors, which shows their limited capacity to capture the underlying patterns in the data. In this case, Gradient Boosting is the best machine learning technique for modeling the complex relationships of the 4 factors influencing reusability potential.

5.2.4 Model Prediction

Figure 8 illustrates the predicted versus actual reuse for the best-performing model: the Gradient Boosting model. The model was trained on the available project dataset and then tested on four projects that were not used in training:

- **HEG0102** – quay wall (completed)
- **NHG0301** – quay wall (completed)
- **Snoekjesbrug** – bridge (completed)
- **Herengracht 101** – quay wall (completed)

For each of these projects, the 4 factors were fed into the trained model to generate a predicted reuse value. These predicted values were then compared with the actual reuse values of the projects. This comparison enables an assessment of how accurately the model can generalise its learned patterns to unseen projects. The results are shown in Figure 8. The blue data points shown in the graph represent each of these tested project's predicted reuse and actual reuse value of the Gradient Boosting ML model.

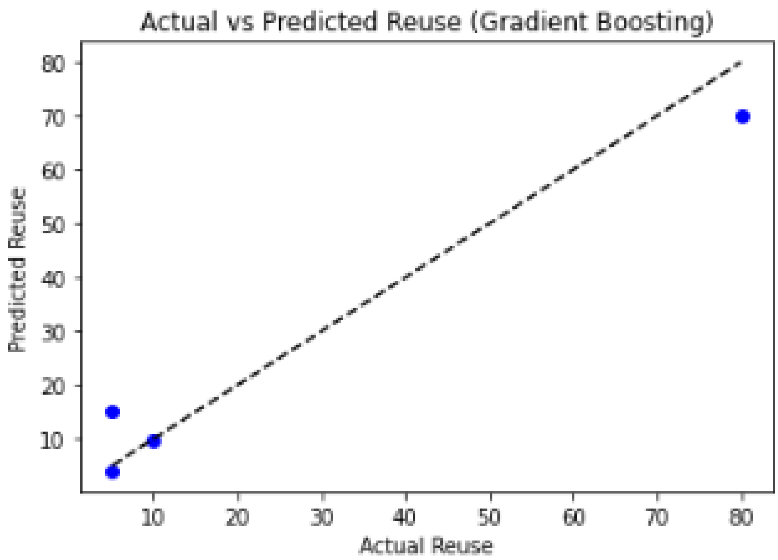

Figure 8: Actual vs. Predicted Reuse for Gradient Boosting ML model

5.3 Results

The results of the machine learning model training and testing provide crucial insights into the key factors influencing material reuse in urban renovation projects. By integrating both the actual reuse as well as the data for the 4 factors in the training set of the machine learning model, the model has identified which factors have the greatest impact on successful material reuse.

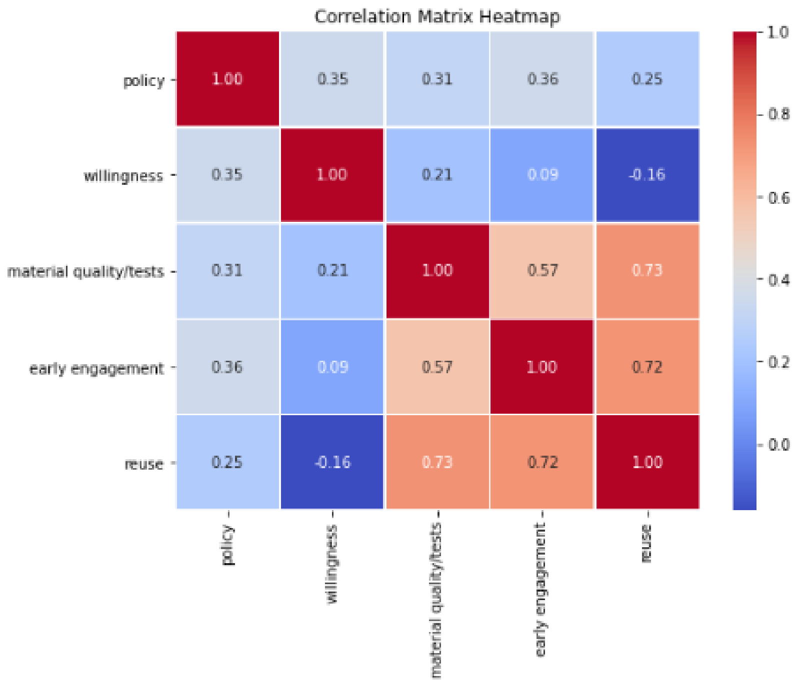

Figure 9: Correlation matrix

Figure 9 presents the correlation matrix, which highlights the relationships between key factors and reuse. The strongest correlations are observed between material reuse and material quality (correlation coefficient = 0.73) and early stakeholder engagement (correlation coefficient = 0.72). In contrast, reuse policy and stakeholder willingness show weak correlations with reuse, suggesting that while these organizational factors are necessary, they may not directly influence reuse outcomes as strongly as the other two factors.

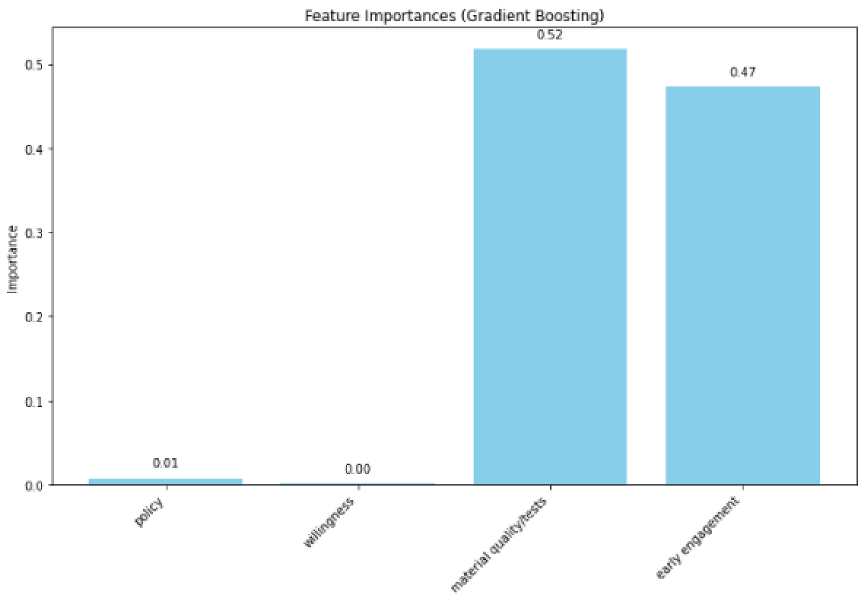

Figure 10: Feature Importance of Factors Influencing Reuse in Gradient Boosting

Figure 10 further illustrates the relative importance or coefficients of these factors for selected Gradient Boost ML model. Similarly to the correlation results, the two factors material quality/testing and early engagement have the highest importance within the Gradient Boost model. Interestingly, the factor willingness has an importance of 0.00, and the factor reuse policy has an importance of 0.01 within the Gradient Boosting model. This means that the model took these factors into little account for the prediction of the reuse.

5.4 Validation

The selected model's predictions were validated through insights from the interview with stakeholders involved in the projects as well as with a follow up validation interview with 2 experts from the Municipality. This qualitative validation helped confirm that the model's findings align with real-world experience and support the practical applicability of the results.

The findings from the machine learning model demonstrate that material quality/testing and early engagement of stakeholders constitute the most significant factors influencing the reusability potential of materials in the renovation projects analyzed. This corresponds closely with qualitative insights from both the stakeholder interviews and the expert validation. Experts emphasized that early engagement gives stakeholders more time to consider and plan for reuse, increasing the likelihood of its successful application. In contrast, when stakeholders are involved later in the process, key decisions about project methods are often already made, limiting opportunities to incorporate reuse. However, the experts also noted that earlier engagement and the implementation of reuse strategies typically require more time, which may act as a practical constraint.

Factors like reuse willingness and policy particularly in projects involving the same stakeholders, exhibited limited variation across different projects, irrespective of the varying percentages of material reuse achieved. This suggests that while these are consistent prerequisites, their direct influence on reuse outcomes may be less pronounced compared to technical factors. The presence of reuse or sustainability in policy requirements is still recent which could explain why there is less variation in the data. In addition, stakeholder willingness is difficult to objectively assess, as it often relies on self-reported attitudes of the stakeholders. Due to the subjective nature of the scores of willingness, this may not lead into actual implementation of reuse, especially when other barriers such as cost or time arise. Lastly, experts noted that instead of a factor with possible subjective scores, experience with reuse could be interesting to include, since a lack of experience and unawareness of the reuse methods to be used also plays a role in material being reused in practice.

Nonetheless, policy remains a critical enabling factor. It provides the structural and procedural framework necessary to support reuse practices. Therefore, although factors such as material quality/testing and early engagement of stakeholders have a more direct and measurable impact on reusability, the presence of a reuse policy is critical to encourage and enforce reuse to other stakeholders by the government, municipality.

5.5 Answering Research Question 3

The results above directly address Research Question 3: Which factors most effectively influence the successful assessment and application of material reuse in sustainable renovation projects?

The results of the Gradient Boosting ML model, as well as the stakeholder interviews and validation with experts show that technical factors, especially material quality and testing, along with early stakeholder engagement, have the strongest and most direct impact on material reuse outcomes. These factors have the highest correlation with reuse, and correspondingly also hold the greatest feature importance in the Gradient Boosting model showing their impact in predicting reusability potential.

On the other hand, organizational factors such as reuse policy and stakeholder willingness demonstrated limited variation across projects involving similar stakeholder groups and therefore contributed less to explaining differences in reuse success. While these factors appear less impactful in the ML model, they remain fundamental as enabling conditions that provide the necessary institutional framework and motivation for reuse in practice. Their presence ensures a supportive environment where reuse can be pursued, even if they do not directly translate into measurable differences in reuse performance in a quantitative model.

It is important to note that while this research, and the performed machine learning analysis focused primarily on technical and stakeholder-related factors, other critical aspects such as cost, project time constraints, and environmental impact (CO_2 emissions) also play significant roles in decisions around material reuse. Future models could incorporate these additional factors to provide a more comprehensive understanding of the trade-offs and drivers influencing reuse in sustainable renovation projects.

In summary, successful material reuse depend primarily on material quality and testing, and engaging stakeholders early in process, while policy and willingness act as essential but more indirect enablers. This nuanced understanding highlights the importance of addressing both technical and organizational dimensions to enhance circularity in urban infrastructure renovation.

6 ML for Future Reusability

This section addresses the fourth research question of this study:

> **RQ4: How can machine learning be used for predicting reusability potential in future projects?**

The section presents insights from the machine learning (ML) model developed in Chapter 5, combined with stakeholder perspectives gathered through interviews. These findings inform how ML can be practically implemented in future renovation projects to support circular decision-making in the City of Amsterdam.

6.1 ML Model as a Predictive Tool

The ML model developed in this research demonstrates that certain features such as material quality and early engagement of stakeholders can serve as useful predictors of reusability potential. These predictors offer a data-driven basis for assessing how much reusability is likely to be possible in certain projects.

Stakeholders noted that such models could become increasingly valuable if applied beyond a single project. Rather than being confined to project-level use, the ML model could be scaled into a city-wide tool by linking it to a shared database of infrastructure data. This would enable continuous learning and model refinement.

At the same time, experts emphasized during validation of the ML model that for the model to truly support decision-making in practice, it should go beyond technical and stakeholder-related inputs. Including broader considerations like cost-benefit analyses, time constraints, and environmental impact would make the tool more reflective of the real-world trade-offs involved in reuse decisions. A more complete and holistic model would help stakeholders balance practical, economic, and sustainability goals when planning for reuse in future renovation projects.

6.2 Toward an Area-Based Strategy

Several interviewees advocated for shifting from a project-by-project reuse strategy toward an areaalbenadering (area-based approach). This approach allows the ML model to assess reuse potential across the entire city, not just within individual project boundaries.

For instance, a bridge component deemed reusable in one project could fulfill a material need in a different quay wall project elsewhere in Amsterdam. An ML model trained with a city-scale dataset could help identify such cross-project reuse opportunities, improving material efficiency and reducing waste.

6.3 Integration into the Design Phase

A key insight from stakeholders was the need to incorporate reusability considerations early in the design phase of new infrastructure. Machine learning can support this by predicting future reusability outcomes based on today's design decisions, such as material selection, component dimensions, or connection types.

Integrating ML into early-stage planning allows for designing with reuse in mind, thereby promoting long-term circularity. This anticipatory approach ensures that future renovation efforts can more easily identify components suitable for reuse.

6.4 Live Databases and Reuse Marketplaces

Another key recommendation was the development of a live, city-wide digital platform that visualizes reusable materials. Stakeholders envisioned a system that links the demand and supply of materials, enabling more effective reuse matching.

Such a platform could include:

- Technical data (e.g., year of production, material type, condition)
- Reusability status and inspection results
- Cost-benefit tools to compare reuse versus replacement
- Storage availability and logistics information

This would allow stakeholders to avoid unnecessary long-term storage, reduce waste, and improve the financial viability of reuse by presenting a clear business case.

6.5 Cross-Project Collaboration and Data Sharing

Stakeholders stressed that broader collaboration is essential for ML to effectively support reuse decisions. Currently, reuse data and practices are often isolated within individual projects or organizations. By promoting cross-project data sharing and common standards, Amsterdam could unlock more robust ML models and enable circular practices at scale.

Cross-Project collaboration would allow:

- Shared learning from successful reuse cases
- Consolidation of material status data across contractors
- Scaled training data for improved ML performance

6.6 Answering Research Question 4

In response to Research Question 4, this study finds that machine learning can support reusability predictions in future projects by identifying influential factors and enabling data-driven decision-making. However, to maximize the model's usefulness, it should be embedded in a larger ecosystem involving:

- A shift to an area-based reuse strategy across the city
- Integration of reuse forecasting in the early design phase
- Development of a live digital platform linking supply and demand
- Cross-project collaboration and open data exchange

When supported by these systemic enablers, ML becomes more than a technical tool. It becomes a strategic asset for circular infrastructure planning in cities like Amsterdam.

7 Discussion

This study aimed to explore the factors influencing the reusability potential of construction elements in the renovation of Amsterdam's bridges and quay walls. While the results from interviews, case studies, and the machine learning-based QCA model provide valuable insights, there are several limitations and considerations that must be acknowledged when interpreting the findings.

7.1 Data Availability and Limitations

One of the key challenges encountered in this research was the limited availability of high-quality data. Although detailed information was collected through interviews and case studies, critical datasets such as reusability scans and condition assessments (e.g., NEBEST scans) were not consistently available across all projects. This inconsistency potentially limited the depth of technical analysis.

The overall sample size was also a constraint. The ML model was built using data from 16 projects, with 4 additional projects used for testing. Although sufficient for initial exploration, this is a relatively small dataset for machine learning analysis. A larger dataset would allow for greater variability in factor combinations and more robust model training and validation. As more renovation projects are assessed in the future, expanding the dataset could significantly improve the model's predictive power and generalizability.

It is also important to consider the project types considered for training and testing the ML model: 17 quay walls and 3 bridges. These two types of structures have several differences in the materials used, renovation methods, the technical requirements for reuse, and the renovation process itself. These differences likely help explain why the bridge projects showed higher percentages of material reuse than the quay wall projects. Furthermore, two of the three bridges were life extension projects rather than full renovations, which may have made reuse more feasible in those cases. As a result, this variation in project types should be taken into account when interpreting the model's findings. This highlights an opportunity for future research to refine the model by training it separately on larger, more homogeneous datasets (only quay walls or only bridges) to improve this limitation.

7.2 Model Scope and Generalizability

This study primarily focused on two types of influencing factors: technical characteristics (such as material quality and testing) and organizational/stakeholder-related conditions (such as early engagement, policy and willingness to reuse)

The model developed in this study is based exclusively on renovation projects in Amsterdam, specifically the city's historical bridges and quay walls. While this narrow focus ensures high contextual relevance, it limits the model's applicability to other cities or types of infrastructure. Amsterdam presents unique conditions like the strict heritage protection requirements and other specific urban constraints like tree preservation Therefore, caution should be exercised when applying the model to different contexts. However, the model can be expanded with additional data from other cities and infrastructure types, allowing for broader applicability and the inclusion of new or modified factors as needed.

A significant limitation of the current model is the exclusion of economic and environmental variables such as cost benefit analysis results, project budget constraints, time constraints and CO_2 emissions. Validation interviews with experts showed that these factors are also critical in decisions around reuse but were not included in the machine learning analysis due to data limitations and the study's focus on technical and stakeholder-related dimensions. As a result, the current model provides a partial perspective, one that is valuable for understanding core technical and organizational drivers but not fully representative of the broader decision-making context.

Future research should aim to incorporate these economic and environmental dimensions, enabling a more comprehensive understanding of the trade-offs involved in reusability decisions. Doing so would enhance the model's practical relevance and support more holistic circular renovation strategies.

7.3 Methodological Considerations

Machine learning was used in this study to identify and compare key factors influencing reusability potential. An alternative approach could have been utilizing simple linear regression, given the relatively small sample size of the data. However, machine learning models were selected to allow for non-linear relationships and interactions between variables. As more data becomes available and the number of influencing factors increases, machine learning approaches are expected to offer more flexibility and improved performance over traditional statistical methods, as proven through the model selection where the Gradient Boosting model had higher accuracy and least error compared to linear regression.

7.4 Stakeholder Bias and Data Interpretation

Another consideration is the potential for bias in stakeholder interviews. Some interviewees appeared to present overly favorable views of their own organization's efforts toward reusability, describing their practices as already optimized. However, these claims were sometimes contradicted by other stakeholders within the same or related projects. This highlights the subjective nature of interview data and the importance of triangulating findings across multiple sources. Recognizing such bias is crucial when interpreting qualitative insights and integrating them into the model.

7.5 Stakeholder Representation

While the interviews covered different stakeholder groups (like contractors, engineering firms, and the municipality), most participants had a technical background. This gave valuable insights into the practical sides of reuse, but it may have overlooked other important perspectives. In future research, involving stakeholders focused on finance, planning, sustainability, or even community needs could bring in different priorities, such as cost, time, environmental impact, etc. This would help build a more complete picture of what drives or limits reuse in practice.

7.6 Future Directions

To strengthen the model and findings, future work could focus on expanding the dataset to include additional renovation projects from different contexts, incorporating more comprehensive factors and data on economic factors, time constraints and environmental impact. In addition, applying the model in other urban infrastructure projects could test and improve whether the results can be generalized, and even uncover new factors influencing material reusability potential. Another valuable direction would be to refine the model by training it on more homogeneous project types, like only quay walls or only bridge projects, allowing for more specific insights.

8 Conclusion

This study explored the following main research question:

Main Research Question: *How can Machine Learning enhance the reusability potential assessment for the sustainable renovation of Amsterdam's bridges and quay walls?*

To answer this, the study combined a literature review, stakeholder interviews, and the development of a machine learning model based on data from 20 completed and ongoing renovation projects. The research provides both conceptual and practical insights into the role of data, stakeholder dynamics, and predictive analytics in material reuse decisions.

8.1 Research Question 1: What information and data are available for assessing reusability potential and preparing the pre-deconstruction audit, and how do different stakeholders influence the assessment of reusability potential?

Reusability potential is shaped by both technical data and stakeholder dynamics. Key technical inputs include the material condition, historical drawings, visual inspections, damage reports, and material testing. These form the basis for evaluating the physical condition of elements prior to potential reuse. However, reusability is not determined by technical data alone.

The findings of the stakeholder interviews show that stakeholders influence reuse potential through several roles. The municipality defines project scopes and sustainability goals; engineering firms carry out technical evaluations; and contractors assess feasibility during implementation. Political priorities, aesthetic considerations, and public perspectives further shape decisions around what can be reused. Challenges include fragmented responsibilities and limited standardization in data and assessment practices. These can be addressed through improved collaboration, clearer roles, and shared digital frameworks.

8.2 Research Question 2: Which factors are most important to stakeholders for reusability?

Interviews and factor-ranking exercises revealed four key factors that stakeholders consider critical for reusability:

- **Reuse policy**

- **Willingness to reuse**
- **Material quality and testing**
- **Early engagement of stakeholders**

These reflect stakeholder priorities and informed the design of the machine learning model. They highlight the need to balance technical and organizational elements when predicting reusability potential.

8.3 Research Question 3: Which factors most effectively influence the successful assessment and application of material reuse in sustainable renovation projects?

The findings from the machine learning analysis, stakeholder interviews, and expert validation indicate that technical factors, particularly material quality and material testing, as well as early stakeholder engagement have the most direct and measurable influence on successful material reuse. Early stakeholder engagement emerged as a critical factor, reinforcing the importance of involving key actors from the beginning of the project to enable realistic planning and timely assessment of reuse options. These factors not only showed the highest correlation with reuse outcomes but also held the greatest feature importance in the Gradient Boosting model, highlighting their predictive power in assessing reusability potential.

In contrast, organizational factors such as reuse policy and stakeholder willingness displayed limited variation across projects involving similar stakeholder groups. While these factors are essential in establishing the institutional and motivational groundwork for reuse, they appear less influential in explaining differences in reuse outcomes between projects. Their role is to enable reuse to take place, rather than being strong predictors of its actual successful material reuse.

It is important to note that this study focused primarily on technical and stakeholder-related aspects due to the available data. Other important considerations, such as cost-benefit trade-offs, time constraints, and environmental impacts (e.g., CO_2 emissions), were not included in the model but are known to play significant roles in decision-making around reuse. Future research should incorporate these dimensions to provide a more holistic view of the factors that drive or hinder material reuse.

8.4 Research Question 4: How can machine learning models support reusability predictions in future projects?

The machine learning model developed in this study demonstrates that reuse potential can be meaningfully predicted using a combination of technical and organizational data. However, the model's effectiveness depends on its integration into a broader ecosystem of reuse planning. To fully support decision-making, machine learning must be embedded within systems that include:

- Area-based reuse strategies across the city
- Integration of reuse forecasting in early design phases
- A live digital platform linking reuse supply and demand
- Cross-project collaboration and open data exchange

Supported by these systemic enablers, machine learning becomes more than a predictive tool—it serves as a strategic asset in advancing circular infrastructure planning in urban contexts like Amsterdam.

8.5 Conclusion

In conclusion, this thesis demonstrates that when machine learning is aligned with stakeholder priorities and supported by collaborative governance and digital infrastructure, it can enhance the reliability, consistency, and foresight of reusability assessments in sustainable urban renovation projects.

Beyond technical contributions, the study also offers grounded insights into how reusability is approached in practice. Through interviews with real stakeholders ranging from municipal officials and engineers to contractors, this research sheds light on the actual conditions, priorities, and challenges shaping reuse decisions in the projects of the Amsterdam Bridges and Quay Walls. It reveals both the enabling factors and the barriers: from the importance of early engagement and high-quality material data, to governmental constraints and unaligned priorities across stakeholders.

The machine learning models results highlight where efforts should be concentrated. Material condition and early stakeholder involvement emerged as the strongest predictors of reuse, highlighting them as key factors for future improvement. While the current model focuses on technical and organizational data, expanding it to include economic, environmental, and time-related dimensions will allow for more effective and holistic reuse prediction.

Overall, this thesis not only shows that predictive tools like machine learning can play a valuable role in circular infrastructure planning, but also offers practical insights into how reuse is currently assessed, where the real-world barriers lie, and how future strategies can be shaped to support more sustainable renovation practices in Amsterdam and beyond.

9 Recommendations & Next steps

Building on the findings of this research, several recommendations future work can further enhance the understanding and practical application of reusability in sustainable renovation projects.

First, expanding the dataset to include a wider variety of renovation projects and more detailed types of factors not only limited by technical and organizational factors, but also including economic, environmental, time and logistics. This can help improve the reliability and predictive ability of machine learning models. Having more and diverse data will also allow for better validation and make the models more applicable beyond the Amsterdam context. It would be useful to test and adapt the model with other projects from other cities and for different types of infrastructure. This will help determine how well the approach works in different environments. Another possible angle would be to refine the model by focusing on one type of project at a time, such as only quay walls or only bridges, which could lead to more specific insights for each.

Ongoing engagement with stakeholders is crucial throughout this process. Future research should involve a broad range of actors to confirm the findings, reduce potential biases, and collaboratively develop clearer criteria for reuse. Encouraging collaboration between stakeholders and open data sharing between projects can improve reusability and lead to better reuse outcomes on a larger scale.

In addition, practical application would benefit from the development of digital platforms that combine material databases, reuse marketplaces, and predictive machine learning tools. These systems can make circular decision-making easier and support reuse strategies at the city level. Embedding reuse requirements into contracts and policies will also help establish circular practices and encourage their adoption.

Finally, future studies could investigate the social, economic, and environmental impacts of reuse decisions and explore how community perspectives can be integrated into the assessment process. Long-term monitoring of circular renovation projects will provide valuable insights into the real-world advantages and challenges of using data-driven reuse strategies.

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A Appendix

A.1 Interview structure

1. **Introduction (2 minutes)**
   - **Objective**: Explain the purpose of the interview and provide a brief overview of the research and confidentiality.
   - **Suggested script**:
     - This interview is part of my master's thesis at TU Delft, which focuses on how machine learning can enhance the the reusability potential assessment in the renovation of Amsterdam's bridges and quay walls.
     - The goal is to better understand how data and stakeholders influence reusability potential in practice. And your insights will help identify key factors for the machine learning model.
     - The interview will take about an hour. Everything you share will be treated confidentially and anonymized in the final report.
     - If you consent, I would like to record the interview for analysis purposes only.
2. **Background of Interviewee (5 minutes)**
   - **Objective**: Understand the interviewee's role and experience.
   - **Questions**:
     - Can you briefly describe your role and responsibilities in the [bridges/quay walls] renovation projects?
3. **Reuse in Practice (10 minutes)**
   - **Objective**: Identify what materials were reused, how much, and where.
   - **Questions**:
     - What materials were reused in this project?
     - How much material was reused?
     - Where were these materials reused? For what purpose?

- Were they reused in the same project or another one?

4. **Information/Data for Assessing Reusability (15 minutes)**
   - **Objective**: Understand what data is used, collected, and shared.
   - **Questions**:
     - What types of data are collected during pre-deconstruction audits?
     - In your experience, which information is most crucial for assessing material reusability?
     - Are there data points that are difficult to obtain? Why?
     - At which stages of the project should or can data be gathered?
     - How is the data documented, analyzed, and shared with stakeholders?
5. **Stakeholder Influence (10 minutes)**
   - **Objective**: Explore stakeholder roles and influence on reusability.
   - **Questions**:
     - Who are the key stakeholders involved in the reusability assessment process?
     - How do these stakeholders influence data collection or reuse decisions?
     - Have you observed any conflicts or alignments of interest around reuse?
6. **Challenges and Opportunities (5 minutes)**
   - **Objective**: Discuss barriers and potential improvements.
   - **Questions**:
     - What challenges do you face in assessing reusability potential?
     - What improvements could make the process more effective?
7. **Ranking Key Factors (to be completed after interview)**
   - **Objective**: Identify which factors are most important for assessing reusability.
   - You will receive a list of technical, functional, and organizational factors identified through literature and case studies. Kindly return the completed form by the next

day.

- **Form questions**:
  - Here is a predefined list of technical, functional, and organizational factors identified through literature review and case studies. Please rate the importance of each factor for reusability potential on a scale from 1 (not important) to 5 (very important).
  - Are there any important factors missing from this list?
  - Which 4 factors are most important in your opinion (and would be interesting for a Machine Learning prediction model that predicts reusability potential)?

A.2 Interview Ranking factors Excel file (English and Dutch)

Classification	Factor	Subfactor	Explanation	Ranking (1-5)
Technical	Standardization	Standard materials	Consistency of materials and standards across projects.	
Technical	Standardization	Component uniqueness	Components with high uniqueness have lower reusability potential due to limited interchangeability.	
Technical	Standardization	Design phase standardization	Standardization should be incorporated during the design phase for future reuse.	
Technical	Quality	Material condition	The state of materials (damaged, aged) affects their reusability.	
Technical	Quality	Life expectancy	The expected remaining life of a material before requiring replacement.	
Technical	Quality	Material inspections	Assessing materials through inspections or advanced methods) for quality.	
Technical	Quality	Product documentation	Availability of documentation for material assessment.	
Technical	Quality	Technical requirements (structural)	Ensuring the materials meet the necessary structural safety and technical standards.	
Functional	Disassembly Potential	Component interfaces and connections	Ease of disassembly is determined by the types and simplicity of connections.	
Functional	Disassembly Potential	Design for disassembly	How well materials are designed to be taken apart and reused.	
Functional	Disassembly Potential	Ease of deconstruction	The simpler the process of breaking down components, the higher the reusability.	
Functional	Logistics and Storage	Transportability	The ease with which materials can be transported to new locations for reuse.	
Functional	Logistics and Storage	Storage capacity and location	Availability of suitable storage space for reused materials.	
Functional	Logistics and Storage	Availability and scheduling of materials	Scheduling of when materials are available for reuse and when needed.	
Functional	Logistics and Storage	Storage duration and preservation	The length of time materials can be stored without degradation.	
Functional	Logistics and Storage	Infrastructure	The adequacy of sorting, storage, and transportation infrastructure for material reuse.	
Functional	Logistics and Storage	Sorting and storage facilities	Availability of proper sorting and storage facilities for materials.	
Functional	Logistics and Storage	Transportation logistics	How well transportation logistics are planned and executed for reused materials.	
Organizational	Policy	Pre-demolition audits	Conducting audits before demolition to assess material reuse potential.	
Organizational	Policy	Mandatory regulations for material reuse	Regulations that mandate the reuse of materials to encourage sustainability.	
Organizational	Policy	Knowledge sharing platforms	Platforms for stakeholders to share knowledge and experiences about material reuse.	
Organizational	Policy	Stakeholder awareness and collaboration	Ensuring stakeholders are aware of reuse goals and actively collaborate for better reuse.	
Organizational	Organization	Reuse in Design Process	Incorporating material reuse considerations early in the design process.	
Organizational	Organization	Reuse in Contract	Including reuse goals and commitments in project contracts.	
Organizational	Organization	Components management coordinator	A designated person to manage reusable components and oversee their use in the project.	
Organizational	Organization	Experience with reused materials	The level of expertise in working with reused materials on the team.	
Organizational	Stakeholder	Early engagement	Involving stakeholders (including community) early in the process to align goals and reduce resistance.	
Organizational	Stakeholder	contractors	Concerns about the aesthetics of reused materials affecting their adoption.	
Organizational	Stakeholder	Collaboration	Effective collaboration among stakeholders to promote material reuse.	
Organizational	Stakeholder	Willingness to compromise	The openness of stakeholders to accept reused materials even when compromises are necessary.	
Organizational	Stakeholder	Transparent communication	Clear and honest communication among stakeholders to promote trust and reduce barriers.	
Organizational	Stakeholder	Information exchange	The sharing of important information to facilitate material reuse.	
Organizational	Stakeholder	Risk-sharing	Distributing risks related to material reuse fairly among stakeholders.	
Organizational	Stakeholder	Trust	Trust between stakeholders is key for successful material reuse.	
Organizational	Stakeholder	Reputation	attention, and environmental perception	
Organizational	Stakeholder	Public awareness of reuse	Public knowledge about the benefits of material reuse can drive acceptance.	
Organizational	Stakeholder	Willingness to reuse	client),	

Classificatie	Factor	Subfactor	Beschrijving	Ranking 1-5
Technisch	Standaardisatie	Standaardmaterialen	Consistentie van materialen en standaarden tussen projecten.	
Technisch	Standaardisatie	Uniciteit van componenten	Componenten met hoge uniciteit hebben een lager hergebruikpotentieel vanwege beperkte uitwisselbaarheid.	
Technisch	Standaardisatie	Standaardisatie in ontwerpfase	Standaardisatie moet tijdens de ontwerpfase worden meegenomen voor toekomstig	
Technisch	Kwaliteit	Materiaaltoestand	De staat van materialen (beschadigd	
Technisch	Kwaliteit	Levensverwachting	De verwachte resterende levensduur van een materiaal voordat vervanging nodig is.	
Technisch	Kwaliteit	Materiaalinspecties	Beoordeling van materialen via inspecties of geavanceerde methoden voor kwaliteit.	
Technisch	Kwaliteit	Productdocumentatie	Beschikbaarheid van documentatie voor materiaalbeoordeling.	
Technisch	Kwaliteit	Technische eisen (constructief)	Zorgen dat materialen voldoen aan de nodige structurele veiligheids- en technische	
Functioneel	Losmaakbaarheid	Componentinterfaces en verbindingen	Type en de eenvoud van verbindingen en componentinterfaces	
Functioneel	Losmaakbaarheid	Ontwerp voor demontage	Hoe goed materialen zijn ontworpen om uit elkaar te worden gehaald en hergebruikt.	
Functioneel	Losmaakbaarheid	Eenvoud van deconstructie	Hoe eenvoudiger het proces van het afbreken van componenten	
Functioneel	Logistiek en Opsla	Transporteerbaarheid	Het gemak waarmee materialen naar nieuwe locaties kunnen worden vervoerd voor	
Functioneel	Logistiek en Opsla	Opslagcapaciteit en locatie	Beschikbaarheid van geschikte opslagruimte voor hergebruikte materialen.	
Functioneel	Logistiek en Opsla	Beschikbaarheid en planning van	Planning van wanneer materialen beschikbaar zijn voor hergebruik en wanneer ze nodig	
Functioneel	Logistiek en Opsla	Opslagduur en conservering	De tijdsduur dat materialen kunnen worden opgeslagen zonder kwaliteitsverlies.	
Functioneel	Logistiek en Opsla	Infrastructuur	De geschiktheid van sorteer-	
Functioneel	Logistiek en Opsla	Sorteer- en opslagfaciliteiten	Beschikbaarheid van goede sorteer- en opslagfaciliteiten voor materialen.	
Functioneel	Logistiek en Opsla	Transportlogistiek	Hoe goed de transportlogistiek is gepland en uitgevoerd voor hergebruikte materialen.	
Organisatorisch	Beleid	Pre-sloping audits	Het uitvoeren van audits vóór sloop om het hergebruikpotentieel van materialen te	
Organisatorisch	Beleid	Verplichte regelgeving voor	Regelgeving die hergebruik van materialen verplicht stelt om duurzaamheid te	
Organisatorisch	Beleid	Kennisdeelplatforms	Platforms voor stakeholders om kennis en ervaringen over materiaalhergebruik te delen.	
Organisatorisch	Beleid	Bewustzijn en samenwerking stakeholders	Zorgen dat stakeholders zich bewust zijn van hergebruikdoelen en actief samenwerken voor beter hergebruik.	
Organisatorisch	Organisatie	Hergebruik in ontwerpproces	Het vroegtijdig meenemen van hergebruikoverwegingen in het ontwerpproces.	
Organisatorisch	Organisatie	Hergebruik in contract	Het opnemen van hergebruikdoelen en -verplichtingen in projectcontracten.	
Organisatorisch	Organisatie	Coördinator componentenbeheer	Een aangewezen persoon om herbruikbare componenten te beheren en hun gebruik in het project te coördineren.	
Organisatorisch	Organisatie	Ervaring met hergebruikte materialen	De mate van expertise in het werken met hergebruikte materialen binnen het team.	
Organisatorisch	Stakeholder	Vroege betrokkenheid	Stakeholders inclusief bewoners vroeg in het proces betrekken om doelen af te stemmen en weerstand te verminderen.	
Organisatorisch	Stakeholder	Esthetische zorgen van architecten en	Zorgen over het uiterlijk van hergebruikte materialen die hun adoptie beïnvloeden.	
Organisatorisch	Stakeholder	Samenwerking	Effectieve samenwerking tussen stakeholders om materiaalhergebruik te bevorderen.	
Organisatorisch	Stakeholder	Bereidheid tot compromissen	De openheid van stakeholders om compromissen te maken om materiaalhergebruik te	
Organisatorisch	Stakeholder	Transparante communicatie	Duidelijke en eerlijke communicatie tussen stakeholders om vertrouwen te bevorderen en barrières te verminderen.	
Organisatorisch	Stakeholder	Informatie-uitwisseling	Het delen van belangrijke informatie om materiaalhergebruik te vergemakkelijken.	
Organisatorisch	Stakeholder	Risicodeling	Een eerlijke verdeling van risico's rond materiaalhergebruik onder stakeholders.	
Organisatorisch	Stakeholder	Vertrouwen	Vertrouwen tussen stakeholders is cruciaal voor succesvol materiaalhergebruik.	
Organisatorisch	Stakeholder	Reputatie	De reputatie van het project kan beslissingen over hergebruikte materialen beïnvloeden (bijv. media-aandacht, politieke aandacht, milieuperceptie)	
Organisatorisch	Stakeholder	Publiek bewustzijn van hergebruik	Publieke kennis over de voordelen van materiaalhergebruik kan acceptatie bevorderen.	
Organisatorisch	Stakeholder	Bereidheid tot hergebruik	Bereidheid van projectstakeholders (ingenieurs, aannemers, ontwerpers en opdrachtgevers) om herbruikbare componenten te integreren.	

Table 6: Factors influencing material reusability assessment: Technical, Functional and Organizational

Classification	Factor	Subfactor
Technical	Standardization	Standard materials
	Standardization	Component uniqueness
	Standardization	Design phase standardization
	Quality	Material condition
	Quality	Life expectancy
	Quality	Material inspections
	Quality	Product documentation
	Quality	Technical requirements (structural)
Functional	Disassembly Potential	Component interfaces and connections
	Disassembly Potential	Design for disassembly
	Disassembly Potential	Ease of deconstruction
	Logistics and Storage	Transportability
	Logistics and Storage	Storage capacity and location
	Logistics and Storage	Availability and scheduling of materials
	Logistics and Storage	Storage duration and preservation
	Logistics and Storage	Infrastructure
	Logistics and Storage	Sorting and storage facilities
	Logistics and Storage	Transportation logistics
Organizational	Policy	Pre-demolition audits
	Policy	Mandatory regulations for material reuse
	Policy	Knowledge sharing platforms
	Policy	Stakeholder awareness and collaboration
	Organization	Reuse in Design Process
	Organization	Reuse in Contract
	Organization	Components management coordinator
	Organization	Experience with reused materials
	Stakeholder	Early engagement
	Stakeholder	Visual appearance concern of architects and contractors
	Stakeholder	Collaboration
	Stakeholder	Willingness to compromise
	Stakeholder	Transparent communication
	Stakeholder	Information exchange
	Stakeholder	Risk-sharing
	Stakeholder	Trust
	Stakeholder	Reputation
	Stakeholder	Public awareness of reuse
	Stakeholder	Willingness to reuse

A.3 Interview themes labelling

Interview Theme	Label	Mentions (Interviewees)	Mention Count
Materials Reused	Stones reused	1, 2, 4, 5	4
	Sheet piles reused in other projects	1, 2	2
	Wood reused for art/furniture	3, 4, 5	3
	No reuse of masonry	3, 4, 5	3
Factors Promoting Reuse	Design flexibility	1, 2, 4, 5	4
	Reuse policy introduced in 2024	1, 2, 4, 5	4
	Early quality checks & assessments	1, 2, 4, 5	4
Pre-deconstruction Data	Pile/lifetime/quality investigations	1, 2, 3, 4, 5	5
	Old design drawings (no 3D)	1, 2, 3, 4, 5	5
	Soil/historical/condition studies	3, 4, 5	3
Timing of Data Gatherinɡ	Before design for construction parts	1, 2, 3, 4, 5	5
	Later for public space components	1, 2, 3, 4, 5	5
Barriers to Reuse	Rigid early design decisions	3, 4, 5	3
	Strict design/aesthetic requirements	1, 2, 4, 5	4
	Cost concerns	1, 2, 3, 4, 5	5
	Higher maintenance from reuse	1, 2, 4, 5	4
	Lack of opportunity to reuse	1, 2, 3, 4, 5	5
Stakeholders	Municipality / policy makers	1, 2, 3, 4, 5	5
	Contractors	1, 2, 3, 4, 5	5
	Maintenance team	1, 2, 4, 5	4
	Engineers / Project managers	3, 4, 5	3
	Tree stakeholders	3, 4, 5	3
Stakeholder Interests	City interested in sustainability more thar	3, 4, 5	3
	Asset managers avoid reuse due to maint	1, 2, 3	5
	Younger staff open to reuse	3	1
	Older staff resist reuse	3	1
Decision Making	3-phase process incl. MCA	3, 4, 5	3
	Multiple municipal teams involved	1, 2, 3, 4, 5	5
Stakeholder Impact	Execution method limitations	1, 2, 4, 5	4
	Location restrictions (trees, vibrations etc.	1, 2, 4, 5	4
	Community disturbance considerations	1, 2, 4, 5	4
	Team culture/awareness impact	3, 4, 5	3
Future Enablers	City-wide BIM implementation	1, 2, 3, 4, 5	5
	Investing in Reuse Research	4,5	2
	Shared digital databases (AEP etc.)	1, 2, 3, 4, 5	5
Information Exchange	Within same contractor only	1, 2, 4, 5	4
	Material bank / cross-project ideas	1, 2, 4, 5	4
BIM Use	Use of Revit for 3D modeling	1, 2, 3, 4, 5	5
	Need to upload models to database	1, 2, 4, 5	4
ML Recommendations	Match supply/demand for reused material	1, 2, 3, 4, 5	5
	Estimate reuse potential from age	3, 4, 5	3
	City-wide reuse data model	1, 2, 3, 4, 5	5

A.4 Factors Ranking Result

Classification	Factor	Subfactor	Explanation	interviewee 1	interviewee 2	interviewee 3	interviewee 4	interviewee 5	with 1 = not important and 5 = very important to reusability pc		
Technical	Standardization	Standard materials	Consistency of materials and standards across projects.	3	5	2	5	5	4		
Technical	Standardization	Component uniqueness	Components with high uniqueness have lower reusability potential due to limited interchangeability.	1	3	4	2	2	2.4		
Technical	Standardization	Design phase standardization	Standardization should be incorporated during the design phase for future reuse.	2	5	4	4	5	4		
Technical	Quality	Material condition	The state of materials (damaged, aged) affects their reusability.	4	5	5	5	4	4.6		
Technical	Quality	Life expectancy	The expected remaining life of a material before requiring replacement.	4	4	4	4	4	4		
Technical	Quality	Material inspections	Assessing materials through inspections or advanced methods) for quality.	5	3	3	4	4	3.8		
Technical	Quality	Product documentation	Availability of documentation for material assessment.	5	3	3	3	2	3.2		
Technical	Quality	Technical requirements (structural)	Ensuring the materials meet the necessary structural safety and technical standards.	5	3	3	4	4	3.8	technical factors avg score	3.725
Functional	Disassembly Potential	Component interfaces and connections	Ease of disassembly is determined by the types and simplicity of connections.	2	3	3	3	3	2.8		
Functional	Disassembly Potential	Design for disassembly	How well materials are designed to be taken apart and reused.	2	2	2	3	5	2.8		
Functional	Disassembly Potential	Ease of deconstruction	The simpler the process of breaking down components, the higher the reusability.	2	4	3	4	5	3.6		
Functional	Logistics and Storage	Transportability	The ease with which materials can be transported to new locations for reuse.	2	4	2	2	2	2.4		
Functional	Logistics and Storage	Storage capacity and location	Availability of suitable storage space for reused materials.	3	4	2	2	2	2.6		
Functional	Logistics and Storage	Availability and scheduling of materials	Scheduling of when materials are available for reuse and when needed.	4	4	4	3	3	3.6		
Functional	Logistics and Storage	Storage duration and preservation	The length of time materials can be stored without degradation.	4	4	2	2	3	3		
Functional	Logistics and Storage	Infrastructure	The adequacy of sorting, storage, and transportation infrastructure for material reuse.	4	2	3	3	3	3		
Functional	Logistics and Storage	Sorting and storage facilities	Availability of proper sorting and storage facilities for materials.	4	2	2	3	2	2.6		
Functional	Logistics and Storage	Transportation logistics	How well transportation logistics are planned and executed for reused materials.	3	2	2	2	2	2.2	functional factors avg score	2.86
Organizational	Policy	Pre-demolition audits	Conducting audits before demolition to assess material reuse potential.	4	2	3	4	4	3.4		
Organizational	Policy	Mandatory regulations for material reuse	Regulations that mandate the reuse of materials to encourage sustainability.	4	3	3	5	5	4		
Organizational	Policy	Knowledge sharing platforms	Platforms for stakeholders to share knowledge and experiences about material reuse.	4	3	2	3	4	3.2		
Organizational	Policy	Stakeholder awareness and collaboration	Ensuring stakeholders are aware of reuse goals and actively collaborate for better reuse.	3	3	4	2	4	3.2		
Organizational	Organization	Reuse in Design Process	Incorporating material reuse considerations early in the design process.	4	4	4	5	5	4.4		
Organizational	Organization	Reuse in Contract	Including reuse goals and commitments in project contracts.	4	4	3	4	5	4		
Organizational	Organization	Components management coordinator	A designated person to manage reusable components and oversee their use in the project.	4	4	2	1	4	3		
Organizational	Organization	Experience with reused materials	The level of expertise in working with reused materials on the team.	3	4	4	4	4	3.8		
Organizational	Stakeholder	Early engagement	Involving stakeholders (including community) early in the process to align goals and reduce resistance.	3	3	4	3	4	3.4		
Organizational	Stakeholder	Visual appearance concern of architects and contractors	Concerns about the aesthetics of reused materials affecting their adoption.	5	3	1	4	4	3.4		
Organizational	Stakeholder	Collaboration	Effective collaboration among stakeholders to promote material reuse.	4	2	2	3	4	3		
Organizational	Stakeholder	Willingness to compromise	The openness of stakeholders to accept reused materials even when compromises are necessary.	3	2	3	3	5	3.2		
Organizational	Stakeholder	Transparent communication	Clear and honest communication among stakeholders to promote trust and reduce barriers.	2	2	3	3	4	2.8		
Organizational	Stakeholder	Information exchange	The sharing of important information to facilitate material reuse.	4	4	3	4	4	3.8		
Organizational	Stakeholder	Risk-sharing	Distributing risks related to material reuse fairly among stakeholders.	4	3	4	3	4	3.6		
Organizational	Stakeholder	Trust	Trust between stakeholders is key for successful material reuse.	3	3	3	4	5	3.6		
Organizational	Stakeholder	Reputation	The reputation of the project can influence decisions related to reused materials eg: Media coverage, political attention, and environmental perception	2	4	4	4	5	3.8		
Organizational	Stakeholder	Public awareness of reuse	Public knowledge about the benefits of material reuse can drive acceptance.	2	4	2	3	4	3		
Organizational	Stakeholder	Willingness to reuse	Willingness to integrate reusable components by project stakeholders (engineers, contractors, designers and client),	4	4	5	5	4	4.4	organizational factors avg score	3.526315789

A.5 Interview transcript notes

April 9th 2025 in Amsterdam

Interviewee 1: Jack (count and cooper & beens) – worked on 3 pbk projects projectleider

Interviewee 2: Tom (Amsterdam) – projectleider engineering and execution

Project focus in this meeting: Herengracht started 2021 and completed – (reuse requirements start in 2024)

PROJECT	**HERENGRACHT – QUAY WALL**
REUSE	**10%**
WHICH MATERIALS REUSED	Street stones (in this project reused), sometimes sheetpiles they have many and they reuse in other projects
FACTORS IMPACTING THAT WOULD PROMOTE REUSABILITY POTENTIAL	- design flexibility - requirements in design stage - quality check - aesthetic new projects is better because very specific guidelines of the city. - Reuse requirements from city started in 2024
DATA PRE DECONSTRUCTION AUDITS	- Do investigations - remaining lifetime - quality - Investigations on piles - Design drawings - (BIM model is very helpful but they don't have it and need to make from the old design drawings)
DATA GATHERED WHEN	- Data be gathered before design stage for construction parts - for components in the public space, it can be a bit later in design stage
BARRIERS TO REUSE	- Less opportunity to reuse - specific design requirements - what quality is there - Costs - design rules - maintenance more tradeoff

STAKEHOLDERS	- Key stakeholders – maintenance part (100 years) - Contractors - Municipality - politics policy government is main decision maker because the requirements including reuse promotion make or break reuse
STAKEHOLDER INTERESTS	- different goals: aesthetic designers are ok to convince - maintenance teams want cost of maintenance as low as possible because their budget is smallest out of all stakeholders, but if reuse is used more maintenance will be needed - contractors, and engineers want reuse if possible - city makes the requirements and since last year reuse is included, but also many other requirements that make it hard to reuse like aesthetics, lifetime
DECISION MAKING	- Decision making within municipality (there are different teams)
FACTORS IMPACTING REUSE (STAKEHOLDERS)	- During the engineering phase, early engagement of contractors would help. - City conditions execution methods - disturbance to stakeholders - some reusable materials can't be installed in different ways (cannot be reused) - location dependent = closer to city no vibration allowed because disturbance of ppl - if community doesn't face disturbance bc of reuse they are not against it - if it doesn't take much time -> boat tourists have disturbance and have to move for longer time - influence to budget, costs flexibility
FUTURE FACTORS IMPACTING REUSE	- Starting up BIM, share it with project teams, maintenance parts,
INFORMATION EXCHANGE	- c

	- Should upload the newly made 3D project models in AEP database to share with other project teams
BIM	- 3D model in Revit (helps to define different phases) requires you to be more specific. Old design drawings available no 3d models. Should upload in AEP database with current projects models.
ML RECOMMENDATION	- Distance house to ground ML model made can be useful database, make model that can have info for the entire city. sharing collaboration with other contractors in other projects.

May 8th 2025 on Teams

Interviewee 1: Erik (AnteaGroup) – worked on 2 completed (both 0% reuse) pbk projects project manager engineering company samenwerkings overeenkomst. Contract manager. Worked on another bridge 6-7 and 10-15 quay walls ongoing. Kloveniers burgwal contains 5 quay walls and brouwersgracht 6 quay walls.

Interviewee 2:

Project focus in this meeting: GDK0203 started 2022 september start contract and last year before summer 2024 completed – (reuse requirements start in 2024)

PROJECT	GDK0203 – QUAY WALL
REUSE	**0%**
WHICH MATERIALS REUSED	Not reused at all.
FACTORS IMPACTING THAT WOULD PROMOTE REUSABILITY POTENTIAL	- design was already finished - before project the choices were already made - wood was already not good enough - wood reused for other purposes like art and furniture. - Masonry idk how good it was but I think not good enough - Bridge project doesn't have circularity but use special concrete - No reuse required they reuse the whole construction but put in stalen buizen en groutinjectiebuisen.
DATA PRE DECONSTRUCTION AUDITS	- Contructief, quality construction parameters. - remaining lifetime - quality - conditionerende onderzoeken, soil tests, historische gegevens - reports, 3d drawings design.
DATA GATHERED WHEN	- Data be gathered before design stage for construction parts - for components in the public space, it can be a bit later in design stage
BARRIERS TO REUSE	- Less opportunity to reuse - specific design requirements

	- what quality is there - Costs
STAKEHOLDERS	- trees in Amsterdam - Amsterdam employees trees - People living there - Boats -
STAKEHOLDER INTERESTS	- Reusability is a politics decision – they are interested but they are more interested in sustainability than reusability of materials, it is an option but sustainability. - Asset manager of the construction if you reuse stuff it has to be as good as new otherwise more maintenance costs - Management of the program who decides whether reusability is a subject. Zij bepalen het beleid. No requirement
DECISION MAKING	- Decision making in 3 phases: 1 conditioning with MCA for which kind of construction will it be – at the end of that phase it goes to the direction of the program (there are different teams) criteria is technical feasibility, behoud van bomen, money, contract with 6 contractors they choose one of the 6 and they split the work 2. Design phase project managers
FACTORS IMPACTING REUSE (STAKEHOLDERS)	- Decide which materials can be reused, masonry reused can cost more. - contractor does the reuse. - Bridge in Leeuwarden Amsterdam the asset manager didn’t want reuse material bc it cost more for maintenance - awareness and noodzaak aan gemeente om te veranderen.

	- Younger people in the team, oudere mensen hebben resistance its easier to work with and they are used to it. Project managers, engineers, contractors. - Less risky in their project
FUTURE FACTORS IMPACTING REUSE	- Starting up BIM, share it with project teams, maintenance parts,
INFORMATION EXCHANGE	- Concrete beams from another project and reuse them in another location in Amsterdam - Reuse construction materials in another project. - Contractor does it, they harvest - Do investigation if its possible to reuse. - Engineer sees possibilities, sometimes contractor comes first.
BIM	- new 3D model in Revit (helps to define different phases) op basis van wat we hebben voor reusable materials it is more work and new norms not standardised. requires you to be more specific. Old design drawings available no 3d models. - If we design a bridge.
ML RECOMMENDATION	- When was it produced tell you something about chances to reuse it, - Vraag en aanbod bij elkaar brengen en inzichtelijk van reusable materials – je wilt het ook niet heel lang opslaan en er zijn Kosten er is business case. - On a big scale of Amsterdam. - De bruggen die wij gesloopt hebben waren heel oud en de staat is noodzakelijk. Maar waar ga je iets functioneel vervangen of nieuwere bruggen - Real old construction if fits reused its reused for other purposes like art furniture or road foundations. There were some pilots to reuse masonry but its not easy and takes a lot of cost. ML model made can be useful database, make model that can have info for the entire city.

sharing collaboration with other contractors in other projects.

May 21st 2025 on Teams

Interviewee 1: Stefan (witteveen bos) engineering form – projectenleider en technisch manager - 2 ramencontracten overeen 4 bruggen (snoekjesbrug klaar), 2 kademuren

Project focus in this meeting: **NHG0301 – Quay wall** (reuse requirements start in 2024)

Project	**NHG0301 – herengracht (Quay wall)**
Reuse	**5% quay wall, snoekjes brug 80%**
Which materials reused	for quay walls: dekstenen, de vaarding bakstenen hergebruiken. the quay wall part less reused than the road part. bridges: bestaande landhoofd, haal kern metselwerk eruit, nieuwe stalen paal, verwijderd klein onderdeel, dek blijven, vleugelbanden hersteld,. verharding en gebakken stenen kan je herbruiken the wooden poles are usually bad quality monumentale balusters, staanders van de leuningen worden altijd hergebruikt good quality materials are transported to the material bureau of Amsterdam municipality and can be reused
Factors impacting that would promote reusability potential	• Before the project starts choice is made whether it is a prevention and intervention project, this is a renovation project with reuse, or demolition project with completely new materials - material testing - for bridges that are renovated they reuse the whole construction but put in stalen buizen en groutinjectiebuisen. • kespen are reused for other purposes: furniture and other • metselwerk is moeilijk om te hergebruiken • technical status of the materials and quality

Data pre deconstruction audits	• Contructief, quality construction parameters. • geometrie • houten vloer en palen zijn slecht • status metselwerk die in kademuur zit is beperkte hergebuik potential • metselwerk en deskteen kan wel • homogeen materiaal is belangrijk maar is er niet • metswelwerk per steen met voegen, arbeidsintensief om voeg te verwijderen. • keuze sloop en nieuwbouw en renovatieproject • zinkers is slopen • bomen is renovatie • plaatbruggen is anders • bodem onderzoeken, soil tests, historische gegevens • staat van materiaal • intacte materialen
Data gathered when	- in fase 3 (conditionering), fase 4 is design and fase 5 is execution. Data should be gathered in fase 3 before design for no surprises. But if the design is not complete then you can do some tests in fase 4. - for components in the public space, it can be a bit later in design stage
Barriers to reuse	- Less opportunity to reuse - trees - specific design requirements - what quality is there

	- Costs
Stakeholders	- beheerder Amsterdam V&OR verkeer en openbare ruimte - directe invloed aannemers en ingenieursbureaus,in contract reuse requirements and sustainability project teams decide what type of project it is (sloop en nieuwbouw of renovatie) - People living there would like that you do something for sustainability: Participatiemodel omwonenden is er altijd Alleen niet In de besluitvorming voor. - Boats - aannemers liever nieuw materiaal sneller en makkelijker -
Stakeholder interests	• Municipality sets requirements for sustainability, this includes reusabaility if possible (since 2 years ago) • Requirements are flexible • contractor prefers new materials because it is faster and easier than taking into account the reused parts and costs • engineering firms understand that reuse is important and promote it where possible • Ik denk dat de mentaliteit vooral is: renovatie is wat goedkoper, Maar het risico is dat je over 30 jaar nog een keer moet en daar hoeven de hele looptijd. Maar ik denk dat bijna ingenieursbureaus ook het beeld wel leeft van Als je nu eigenlijk

	voor 30 jaar. Nou z zet hem vooral In de monitoring, want Misschien gaat ie wel 60 jaar mee. •
Decision making	- Decision making in 3 phases: 1 conditioning with MCA for which kind of construction will it be – at the end of that phase it goes to the direction of the program (there are different teams) criteria is technical feasibility, behoud van bomen, money, contract with 6 contractors they choose one of the 6 and they split the work 2. Design phase project managers - type of project is chosen through MCA with different parameters like MKI, constructieve haalbaarheid, behoud van bomen, ruimtebeslag. But reusability is not part of this MCA. engineering firms and contractors dont have much influence in decision making about type of project (renovation with reuse) and usually are engaged once the type of project decision is made. Amsterdam creates a BVM (Besluit veiligheids maatregel) which states whether the project is a new build, demolition or renovation.

Factors impacting reuse (stakeholders)	- Decide which materials can be reused, masonry reused can cost more. - willingness of stakeholders for reuse seeing the potential reuse knowing reuse benefits - volgens mij moet moet het op den duur moeten we gewoon heen duurzaam tenzij. Dus zou het eerder andersom moeten zijn. Er moet een goede reden zijn om ervoor af te wijken, maar zo ver zijn we nu gewoon qua methodes ook nog niet.
Future factors impacting reuse	- Starting up BIM, share it with project teams, maintenance parts, over 5 jaar zeggen we gewoon het hergebruik hergebruik van je materialen moet 80% zijn, dus vind maar een herbestemming voor al je materialen. je gaat de kademuur vervangen, dan wil je dus eerst alle informatie van die kademuur hebben. Dan wil je een soort van decompositie hebben. In welke materialen zijn er, welk potentieel hergebruik is er?
Information exchange	- amsterdam sharepoint locaties, - mail. - bim model not shared

BIM	- new 3D model in Revit (helps to define different phases) op basis van wat we hebben voor reusable materials it is more work and new norms not standardised. requires you to be more specific. Old design drawings available no 3d models. - If we design a bridge.
ML recommendation	• status van de materialen • kosten baten • is het waard om reuse? • - Vraag en aanbod bij elkaar brengen en inzichtelijk van reusable materials – je wilt het ook niet heel lang opslaan en er zijn Kosten er is business case. - On a big scale of Amsterdam. - De bruggen die wij gesloopt hebben waren heel oud en de staat is noodzakelijk. Maar waar ga je iets functioneel vervangen of nieuwere bruggen - Real old construction if fits reused its reused for other purposes like art furniture or road foundations. There were some pilots to reuse masonry but its not easy and takes a lot of cost.

May 22st 2025 on Teams

Interviewee 1: Yozef (Amsterdam) – sinds 2019 manager project beheersing binnen integraal project management. sinds 2020 innovatiepartnerschap nieuwe norm is alleen parkeerstrook afgesloten voor overlast. bomen behouden. beperkt herbruikbaarheid, japans system met gyropress buispalen, dekstenen herbruiken.

Project focus in this meeting: SIN0701, bouwegracht, lijnbaansgracht, (3 projects), all 3 completed, cloveniersbrurgwand ongoing (duurzaamheid, energiezuinig, electric machines hijskranen om piekbelasting op te vangen).. oct 2022 start contract and last year before juli 2023 completed – (reuse requirements start in 2024)

Project	**SIN0701– Quay wall**
Reuse	**10**
Which materials reused	dekstenen, straat stenen, zoveel mogelijk grond (maar is moeilijk, voor bomen brengen bomenzand) testen hoe slecht het is. damwanden buiten de stad hergebruikt
Factors impacting that would promote reusability potential	- design was already finished - before project the choices were already made - wood was already not good enough - wood reused for other purposes like art and furniture. - Masonry idk how good it was but I think not good enough - Bridge project doesn’t have circularity but use special concrete - No reuse required they reuse the whole construction but put in stalen buizen en groutinjectiebuisen.

Data pre deconstruction audits	- monitoren, predictie hoe lang die meekan monitorings data (autonome zetting, slechte staat, weersinvloeden), zetting, in een model - satteliet data voor panden want alles in verbinding - waterpijldata (waterniveau in ondergrond met pijlbuizen) - bomen periodiek conditie met fitheid - asset informatie errond - contructie (buispalen, L constructie, combiwand) - opleverdossier met onderhoudbaarheid en constuctie - de moeite versus hoeveel het opbrengt -> conditiecheck van materialen - materialen conditie - esthetische parameters - reuse factors before - plaatbruggen is anderes dan - bodem onderzoeken, soil tests, historische gegevens - gemoetrie - staat van materiaal intact
Data gathered when	- before
Barriers to reuse	- Less opportunity to reuse - specific design requirements - what quality is there - Costs

Stakeholders	- ingenieursbureau volgens beheersorgonasitie VOR geeft wens, - aannemers voor incentive te voeren emmisieloos project intrinsiek vanuit aannemers) - People living there, shops, informeren, during project - Boats - -
Stakeholder interests	- beheerorganisite VOR hebben meeste stem, materiaal moeheid doorslaggevende stemming - hergebruik is goedkoopste en er is een kost - gebiedsplanning VOR wil nieuwe materialen, staat van maaienveld, onderhoudsprogramma - vervangins opgave geen nieuw - goede materialen tijdelijk inzetten in andere projecten - ingenieurs en aannemersmore important, duurzaamheid, cheaper than new, sector wordt steeds groener - herbruik eisen steeds meer duurzaam tenzij,bewonders waarderen oude stenen
Decision making	- bij nulmeting, hoe goed hoe slecht, beslissing door rapport goed genoeg om te hergebruiken beslissing door VOR

Factors impacting reuse (stakeholders)	- awareness sentiment over gebruik - vervoer over water is duur, hoe minder nieuwe hoe goedkoper het is. - challenge within budget do what we gotta do so we want reuse - meer investeren in onderzoek, - open gesprek met aannemer en stakeholders en beheerder - contract belang - constructie op 50, 75 , 100 weer kan uithalen, en terug obouwt -> future engineering ipv reverse engineering
Future factors impacting reuse	- Starting up BIM, share it with project teams, maintenance parts,
Information exchange	- rapport deelt met project team, voor projectenkaart met assets amsterdam depots materials opgeslagen, en andere projecten kunnen gebruik maken ligt op de teemsrecht. projecten doen independent verzoek or sometimes depot says
BIM	- new 3D model in Revit (helps to define different phases) op basis van wat we hebben voor reusable materials it is more work and new norms not standardised. requires you to be more specific. Old design drawings available no 3d models. - If we design a bridge.

ML recommendation	• reusability value in the future of the new asset • bij ontwerpfase • live database van depot Vraag en aanbod bij elkaar brengen en inzichtelijk van reusable materials- • On a big scale of Amsterdam.

A.6 Machine Learning Models: Collected Data (20 Projects) and Python Code

This appendix shows the complete Python Code used to train, test and visualize results of all the machine learning models. The Collected Data (factor scores and reuse percentage) for the different projects including their project codes is displayed. As visible in the code of the ML models, the first 4 projects in the dataframe list were used for testing, and the other 16 were used for training the models.

In [19]:
```
%matplotlib inline

import numpy as np
np.float = float
np.object = object
np.bool = bool
import matplotlib.pyplot as plt
from scipy.stats import norm, lognorm
from scipy.integrate import quad
from scipy.optimize import fsolve
import pandas as pd
import matplotlib.pyplot as plt
import datetime as dt
import seaborn as sns
```

In [20]:
```
df = pd.read_csv('mldata.csv')
display(df.head(20))
```

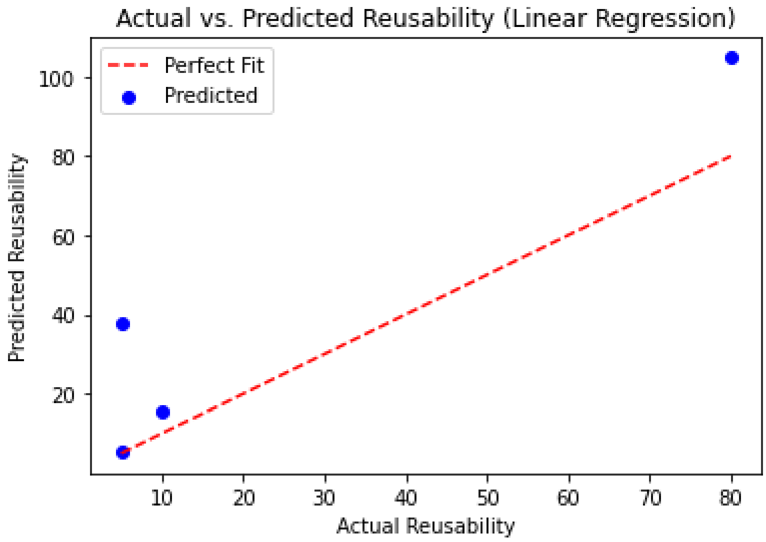
	policy	willingness	material quality/tests	early engagement	reuse	project	type	status
0	2	3.0	2.0	2	10	HEG0102	quay wall	completed
1	2	4.0	2.0	3	5	NHG0301	quay wall	completed
2	4	4.0	5.0	4	80	Snoekjesbrug	bridge	completed
3	4	4.0	2.5	2	5	Herengracht 101	quay wall	completed
4	3	4.0	2.5	2	5	Herengracht 102	quay wall	completed
5	3	4.0	2.5	2	5	Herengracht 103	quay wall	completed
6	4	4.0	2.5	2	15	Prinsengracht 432	quay wall	completed
7	2	3.0	2.5	2	5	KVV0602	quay wall	ongoing
8	2	3.0	2.5	2	5	KVV0702	quay wall	ongoing
9	3	4.0	2.0	2	10	SIN0702	quay wall	completed
10	3	4.0	1.5	2	5	BRG0301	quay wall	completed
11	3	4.0	1.5	2	5	LYG0602	quay wall	completed
12	3	4.0	1.5	2	5	KBW0102	quay wall	ongoing
13	3	4.0	1.5	2	5	KBW0103	quay wall	ongoing
14	4	4.0	1.5	3	4	PGR0801	quay wall	completed
15	4	2.0	1.5	2	0	KVV0405	quay wall	completed
16	4	4.0	1.5	3	2	GDK0203	quay wall	completed
17	2	2.0	1.0	2	5	NHG0201	quay wall	ongoing
18	3	2.5	2.5	3	70	BRU0289	bridge	ongoing
19	3	2.5	2.5	3	80	BRU034	bridge	ongoing

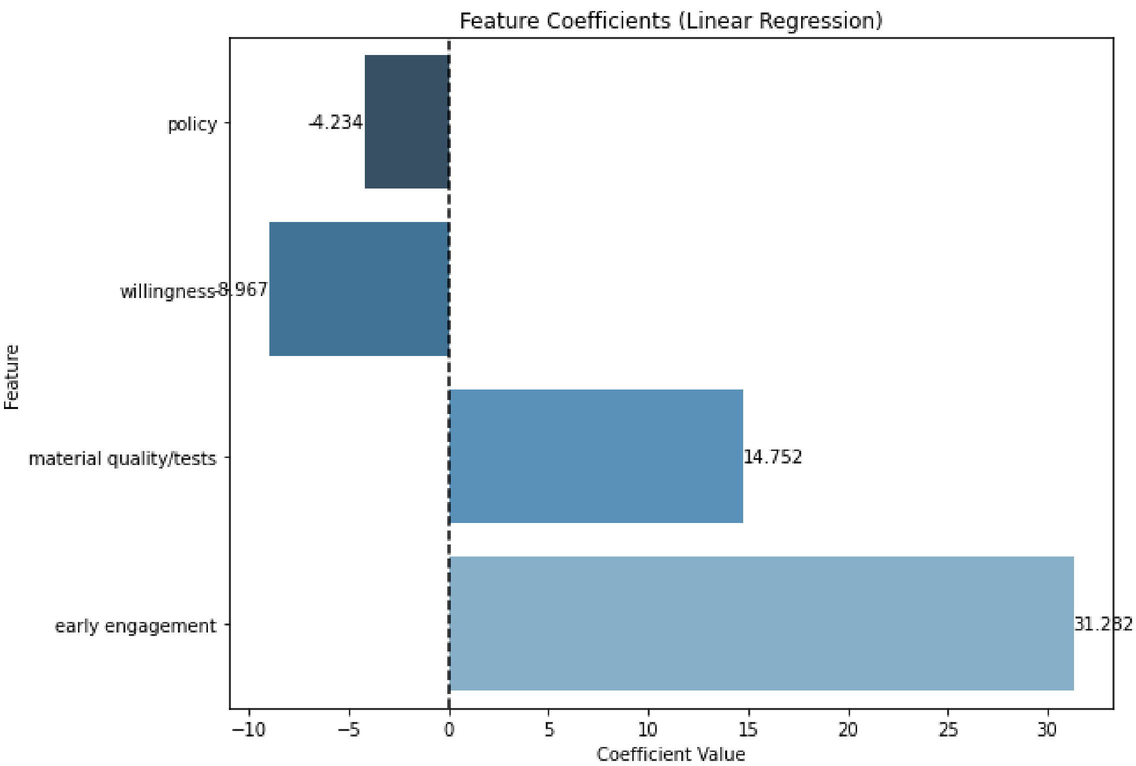
In [3]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, r2_score

# Split the dataset
X_train = df.iloc[4:21, :4]  # Features (Columns 1-4, Rows 5-20)
y_train = df.iloc[4:21, 4]   # Target (Column 5, Rows 5-20)

X_test = df.iloc[:4, :4]     # Features (Columns 1-4, Rows 1-4)
y_test = df.iloc[:4, 4]      # Target (Column 5, Rows 1-4)

# Train Linear Regression model
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)

# Predictions on test data
y_pred = lr_model.predict(X_test)

# Evaluate Performance
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Absolute Error (MAE): {mae:.4f}")
print(f"R² Score: {r2:.4f}")

# Optional: print coefficients
coefficients = lr_model.coef_
features = df.columns[:4]
for feat, coef in zip(features, coefficients):
    print(f"Coefficient for {feat}: {coef:.4f}")


# 1. Scatter Plot: Actual vs Predicted
plt.figure(figsize=(6, 4))
plt.scatter(y_test, y_pred, color='blue', label="Predicted")
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], '--', colo
r='red', label="Perfect Fit")
plt.xlabel("Actual Reusability")
plt.ylabel("Predicted Reusability")
plt.title("Actual vs. Predicted Reusability (Linear Regression)")
plt.legend()
plt.show()

# 2. Plotting Feature Coefficients
coefficients = lr_model.coef_
features = df.columns[:4]

plt.figure(figsize=(9, 7))
ax = sns.barplot(x=coefficients, y=features, palette='Blues_d')
plt.title('Feature Coefficients (Linear Regression)')
plt.xlabel('Coefficient Value')
plt.ylabel('Feature')
plt.axvline(0, color='black', linestyle='--')

# Add coefficient values next to bars
for i, v in enumerate(coefficients):
    ax.text(v, i, f'{v:.3f}', color='black', va='center',
            ha='left' if v > 0 else 'right')
```

```
plt.show()
```

```
Mean Absolute Error (MAE): 15.8378
R² Score: 0.5760
Coefficient for policy: -4.2336
Coefficient for willingness: -8.9673
Coefficient for material quality/tests: 14.7519
Coefficient for early engagement: 31.2824
```



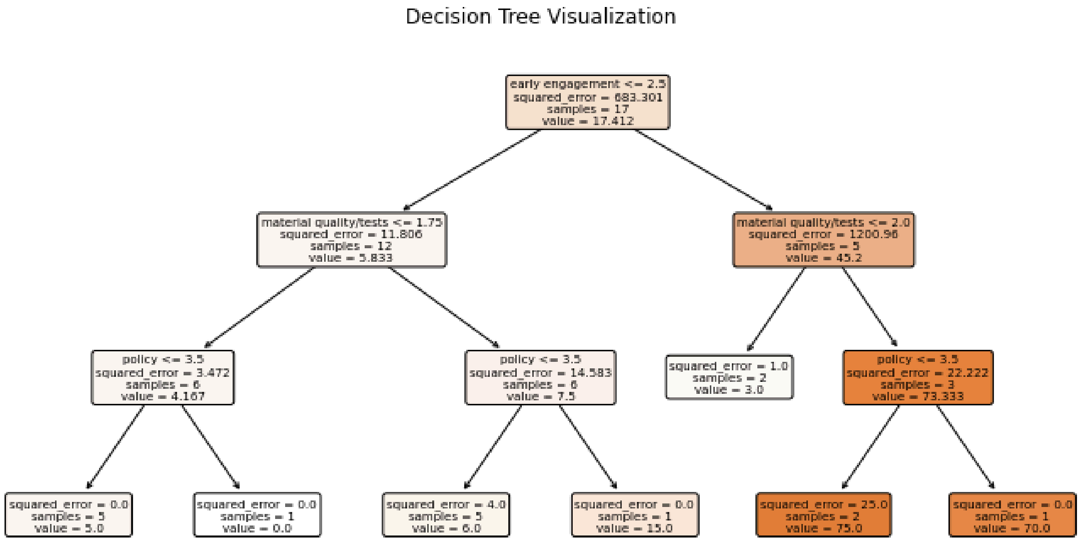


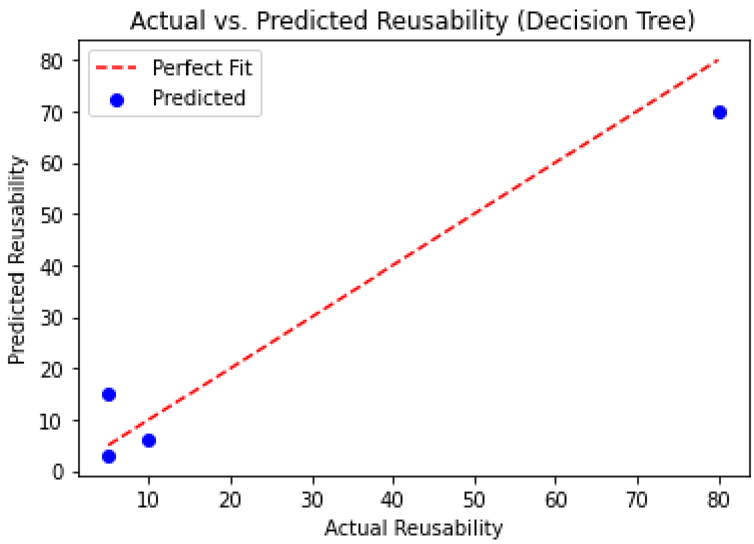
In [4]:

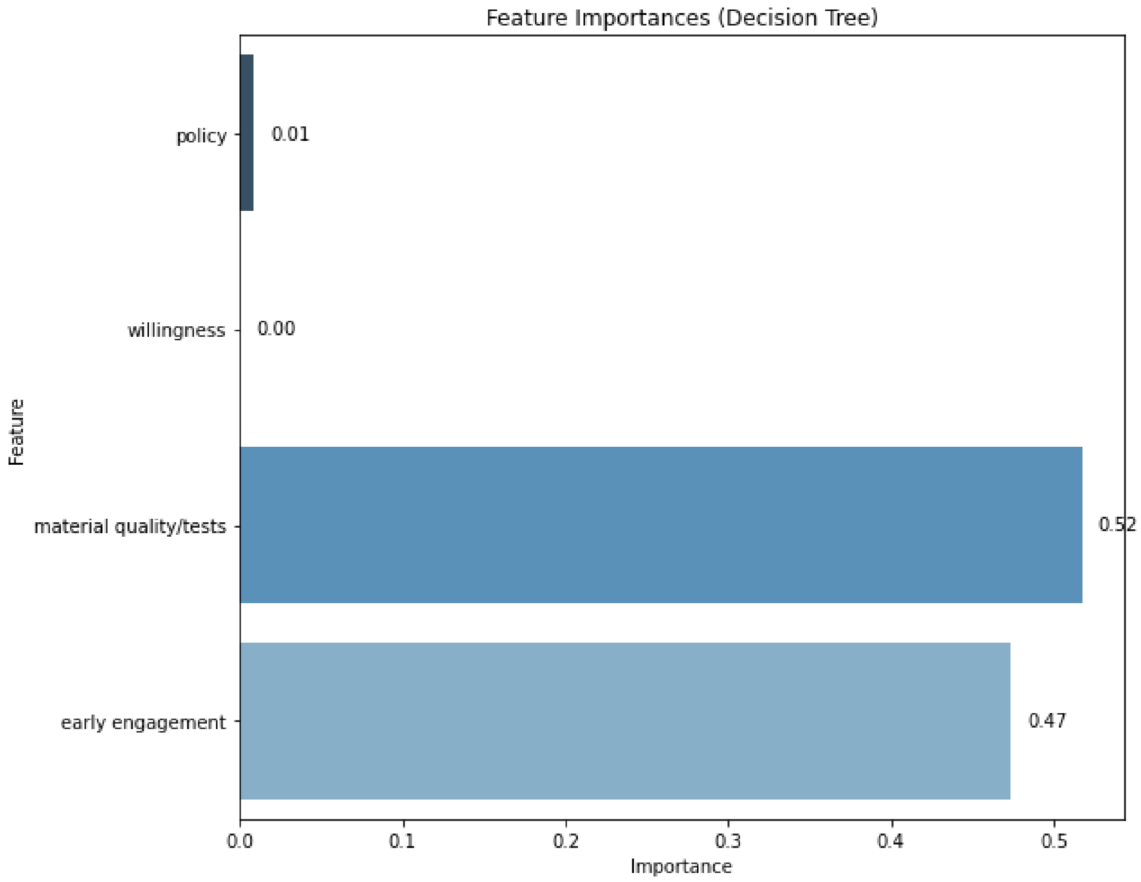
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeRegressor, plot_tree
from sklearn.metrics import mean_absolute_error, r2_score


# Split the dataset
X_train = df.iloc[4:21, :4]  # Features (Columns 1-4, Rows 5-20)
y_train = df.iloc[4:21, 4]   # Target (Column 5, Rows 5-20)

X_test = df.iloc[:4, :4]     # Features (Columns 1-4, Rows 1-4)
y_test = df.iloc[:4, 4]      # Target (Column 5, Rows 1-4)

# Train Decision Tree Regressor
dt_model = DecisionTreeRegressor(max_depth=3, random_state=42)  # Limit dep
th to avoid overfitting
dt_model.fit(X_train, y_train)

# Predictions on test data
y_pred = dt_model.predict(X_test)

# Evaluate Performance
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Absolute Error (MAE): {mae:.4f}")
print(f"R² Score: {r2:.4f}")
```

```
Mean Absolute Error (MAE): 6.5000
R² Score: 0.9457
```

In [5]:
```
# ---- Visualizations ----

# Plot Decision Tree
plt.figure(figsize=(12, 6))
plot_tree(dt_model, feature_names=X_train.columns, filled=True, rounded=Tru
e)
plt.title("Decision Tree Visualization")
plt.show()

# Scatter Plot: Actual vs. Predicted
plt.figure(figsize=(6, 4))
plt.scatter(y_test, y_pred, color='blue', label="Predicted")
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], '--', colo
r='red', label="Perfect Fit")
plt.xlabel("Actual Reusability")
plt.ylabel("Predicted Reusability")
plt.title("Actual vs. Predicted Reusability (Decision Tree)")
plt.legend()
plt.show()

#plotting feature coefficients
feature_importances = dt_model.feature_importances_
features = X_train.columns

plt.figure(figsize=(9, 7))
ax = sns.barplot(x=feature_importances, y=features, palette='Blues_d')
plt.title('Feature Importances (Decision Tree)')
plt.xlabel('Importance')
plt.ylabel('Feature')

# Add importance values next to bars
for i, v in enumerate(feature_importances):
    ax.text(v + 0.01, i, f'{v:.2f}', color='black', va='center')  # added o
ffset for visibility

plt.tight_layout()
plt.show()
```


Decision Tree Visualization
early engagement <= 2.5
squared_error = 683.301
samples = 17
value = 17.412
material quality/tests <= 1.75
squared_error = 11.806
samples = 12
value = 5.833
material quality/tests <= 2.0
squared_error = 1200.96
samples = 5
value = 45.2
policy <= 3.5
squared_error = 3.472
samples = 6
value = 4.167
policy <= 3.5
squared_error = 14.583
samples = 6
value = 7.5
squared_error = 1.0
samples = 2
value = 3.0
policy <= 3.5
squared_error = 22.222
samples = 3
value = 73.333
squared_error = 0.0
samples = 5
value = 5.0
squared_error = 0.0
samples = 1
value = 0.0
squared_error = 4.0
samples = 5
value = 6.0
squared_error = 0.0
samples = 1
value = 15.0
squared_error = 25.0
samples = 2
value = 75.0
squared_error = 0.0
samples = 1
value = 70.0


Actual vs. Predicted Reusability (Decision Tree)
Perfect Fit
Predicted
Predicted Reusability
Actual Reusability
0
10
20
30
40
50
60
70
80

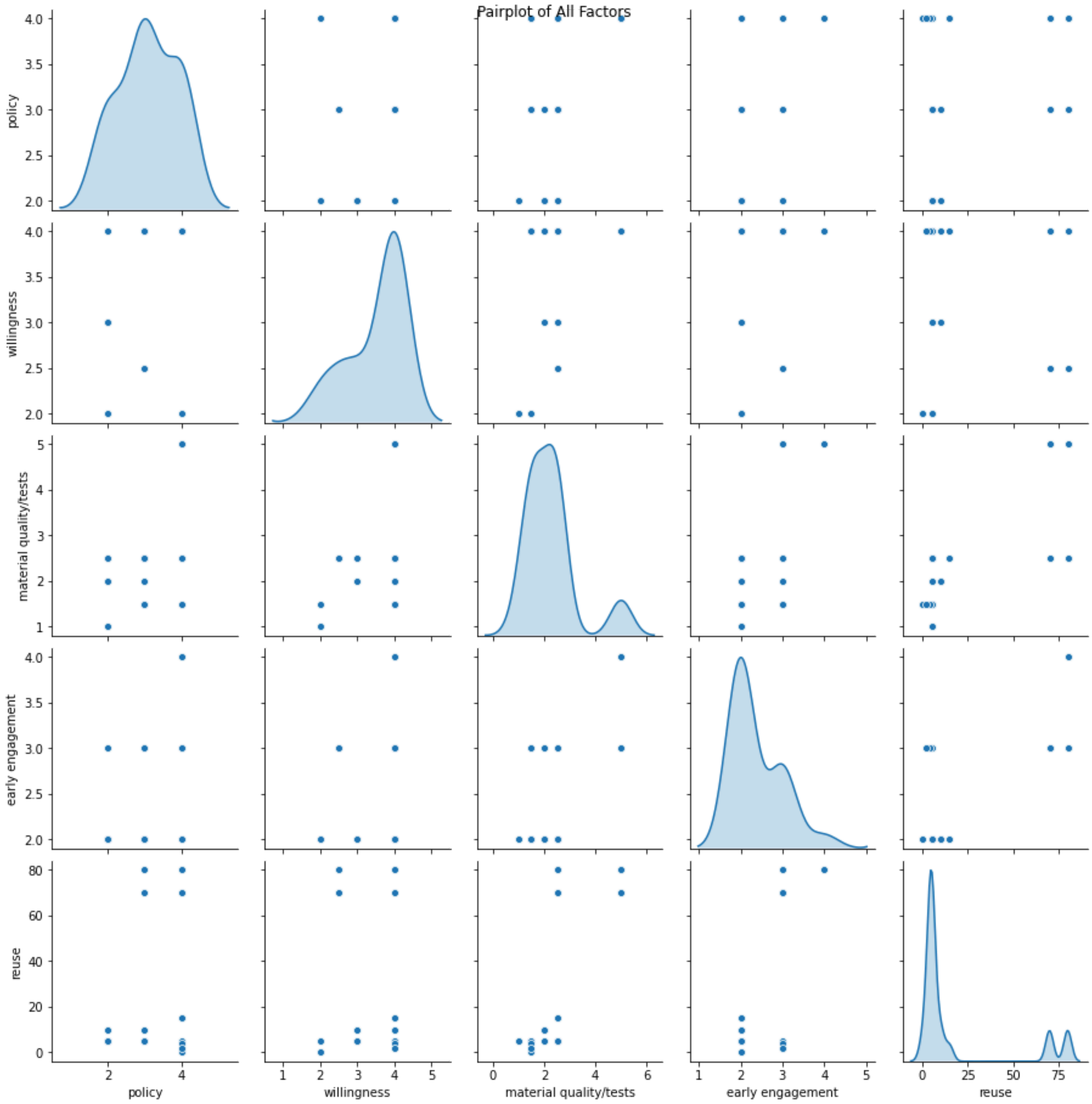


Feature Importances (Decision Tree)
policy
0.01
willingness
0.00
material quality/tests
0.52
early engagement
0.47
Feature
0.0
0.1
0.2
0.3
0.4
0.5
Importance

In [24]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
import numpy as np



# Split the data into training and testing sets
X_train = df.iloc[4:21, :4]  # Features (Columns 1-4, Rows 5-20)
y_train = df.iloc[4:21, 4]   # Target (Column 5, Rows 5-20)

X_test = df.iloc[:4, :4]     # Features (Columns 1-4, Rows 1-4)
y_test = df.iloc[:4, 4]      # Target (Column 5, Rows 1-4)



# Train the Random Forest model
model_rf = RandomForestRegressor(n_estimators=100, random_state=42)
model_rf.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model_rf.predict(X_test)

# Calculate performance metrics
mae_rf = mean_absolute_error(y_test, y_pred)
r2_rf = r2_score(y_test, y_pred)

print('mae is', mae_rf)
print('r2 is',r2_rf)
```

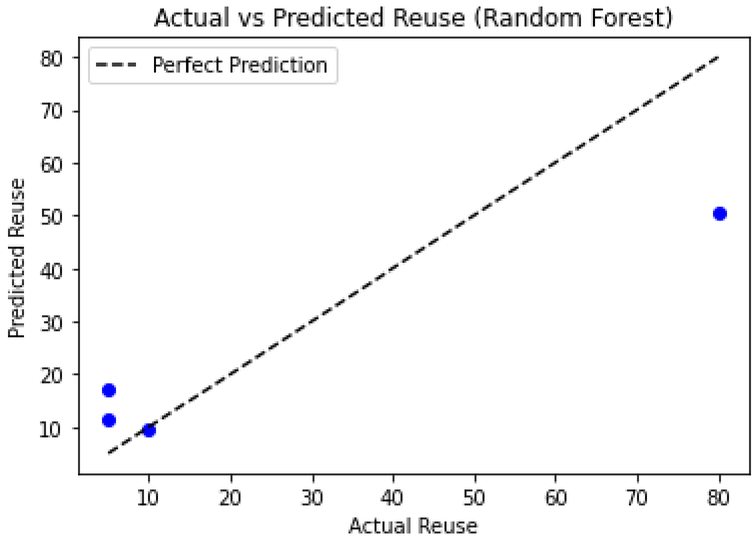
```
mae is 12.146666666666663
r2 is 0.7395154074074075
```

In [8]:
```
# Visualizations
# Pairplot for all factors
sns.pairplot(df, diag_kind='kde')
plt.suptitle('Pairplot of All Factors', y=1)
plt.show()
```

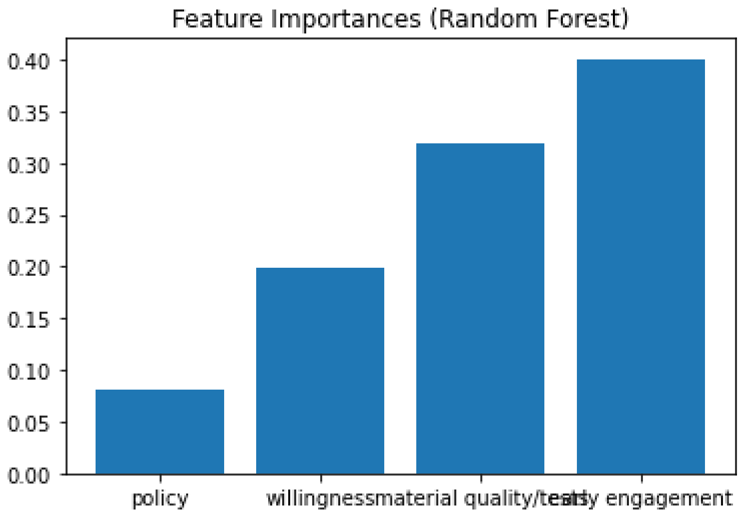


In [ ]:

In [25]:
```
# Scatter plot of predicted vs actual values
plt.scatter(y_test, y_pred, color='blue')

# Calculate correct min and max values
min_val = min(y_test.min(), y_pred.min())
max_val = max(y_test.max(), y_pred.max())

# Plot the perfect prediction line
plt.plot([min_val, max_val], [min_val, max_val], '--k', label='Perfect Pred
iction')
  # Ideal line
plt.xlabel('Actual Reuse')
plt.ylabel('Predicted Reuse')
plt.title('Actual vs Predicted Reuse (Random Forest)')
plt.legend()
plt.show()
```



In [28]:
```python
# Feature importance
feature_importances = model_rf.feature_importances_
plt.bar(X_train.columns, feature_importances)
plt.title('Feature Importances (Random Forest)')
plt.show()

# Print model performance
print(f'Mean Absolute Error (Random Forest): {mae_rf:.4f}')
print(f'R-squared (Random Forest): {r2_rf:.4f}')
```

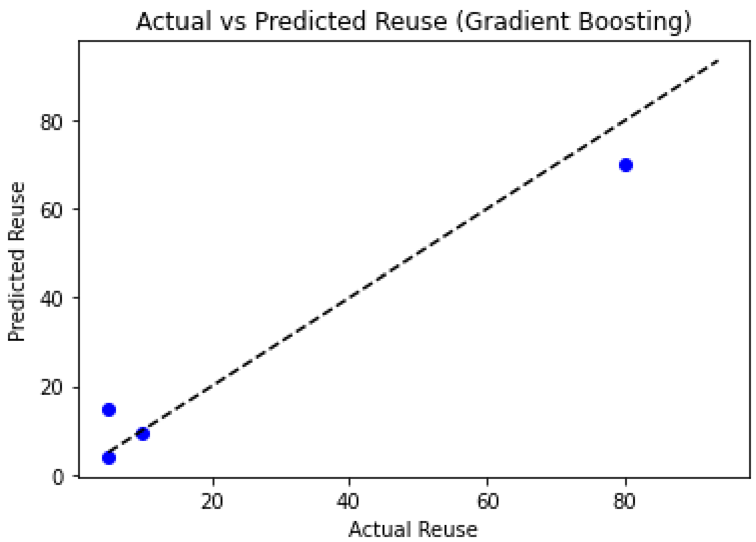


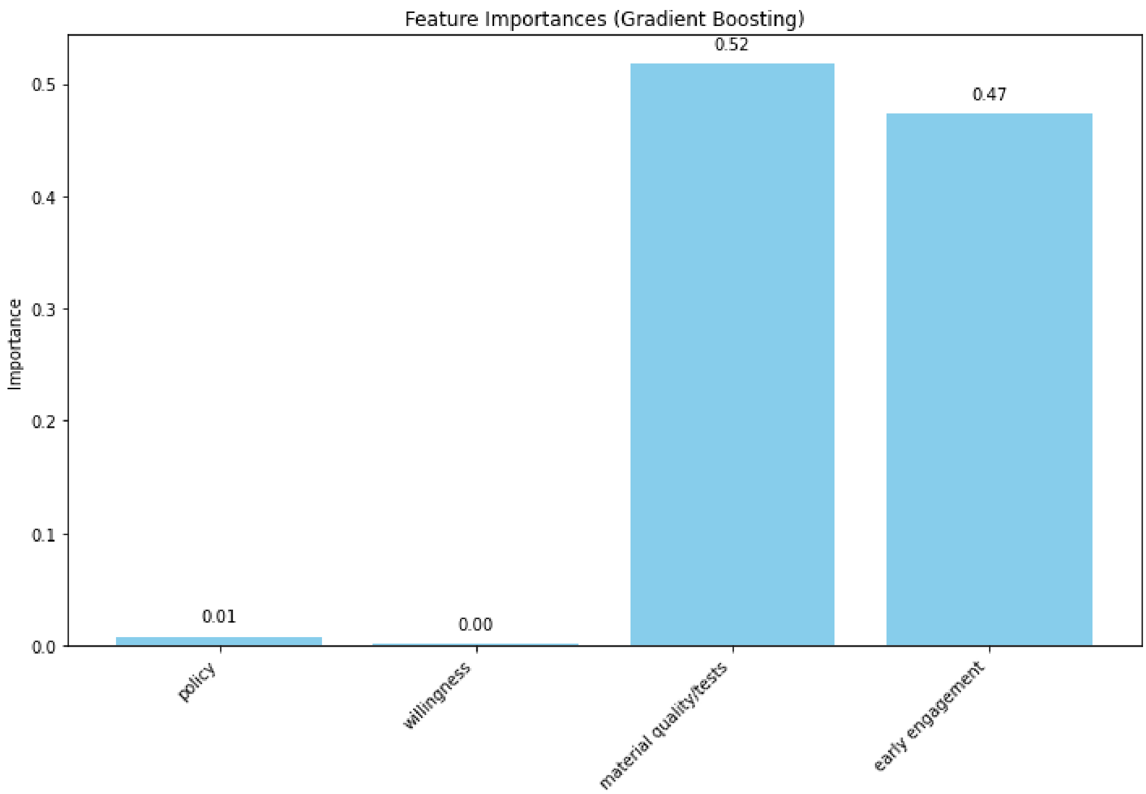

```
Mean Absolute Error (Random Forest): 12.1467
R-squared (Random Forest): 0.7395
```

In [36]:

```python
#GRADIENT BOOSTING
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, r2_score
import numpy as np

# Create the data frame from the provided data

# Split the data into training and testing sets
X_train = df.iloc[4:21, :4]  # Features (Columns 1-4, Rows 5-20)
y_train = df.iloc[4:21, 4]   # Target (Column 5, Rows 5-20)

X_test = df.iloc[:4, :4]     # Features (Columns 1-4, Rows 1-4)
y_test = df.iloc[:4, 4]      # Target (Column 5, Rows 1-4)



# Train the Gradient Boosting model
model_gb = GradientBoostingRegressor(n_estimators=100, random_state=42)
model_gb.fit(X_train, y_train)

# Make predictions on the test set
y_pred_gb = model_gb.predict(X_test)

# Calculate performance metrics
mae_gb = mean_absolute_error(y_test, y_pred_gb)
r2_gb = r2_score(y_test, y_pred_gb)

# Visualizations

# Scatter plot of predicted vs actual values
plt.scatter(y_test, y_pred_gb, color='blue')

# Calculate correct min and max values
min_val = min(y_test.min(), y_pred.min())
max_val = max(y_test.max(), y_pred.max())

# Plot the perfect prediction line
plt.plot([min_val, max_val], [min_val, max_val], '--k', label='Perfect Pred
iction')

plt.xlabel('Actual Reuse')
plt.ylabel('Predicted Reuse')
plt.title('Actual vs Predicted Reuse (Gradient Boosting)')
plt.show()

import matplotlib.pyplot as plt

# Feature importance values
feature_importances_gb = model_gb.feature_importances_
features = X_train.columns

# Plot
plt.figure(figsize=(10, 7))
bars = plt.bar(features, feature_importances_gb, color='skyblue')
plt.title('Feature Importances (Gradient Boosting)')
plt.ylabel('Importance')
plt.xticks(rotation=45, ha='right')
```

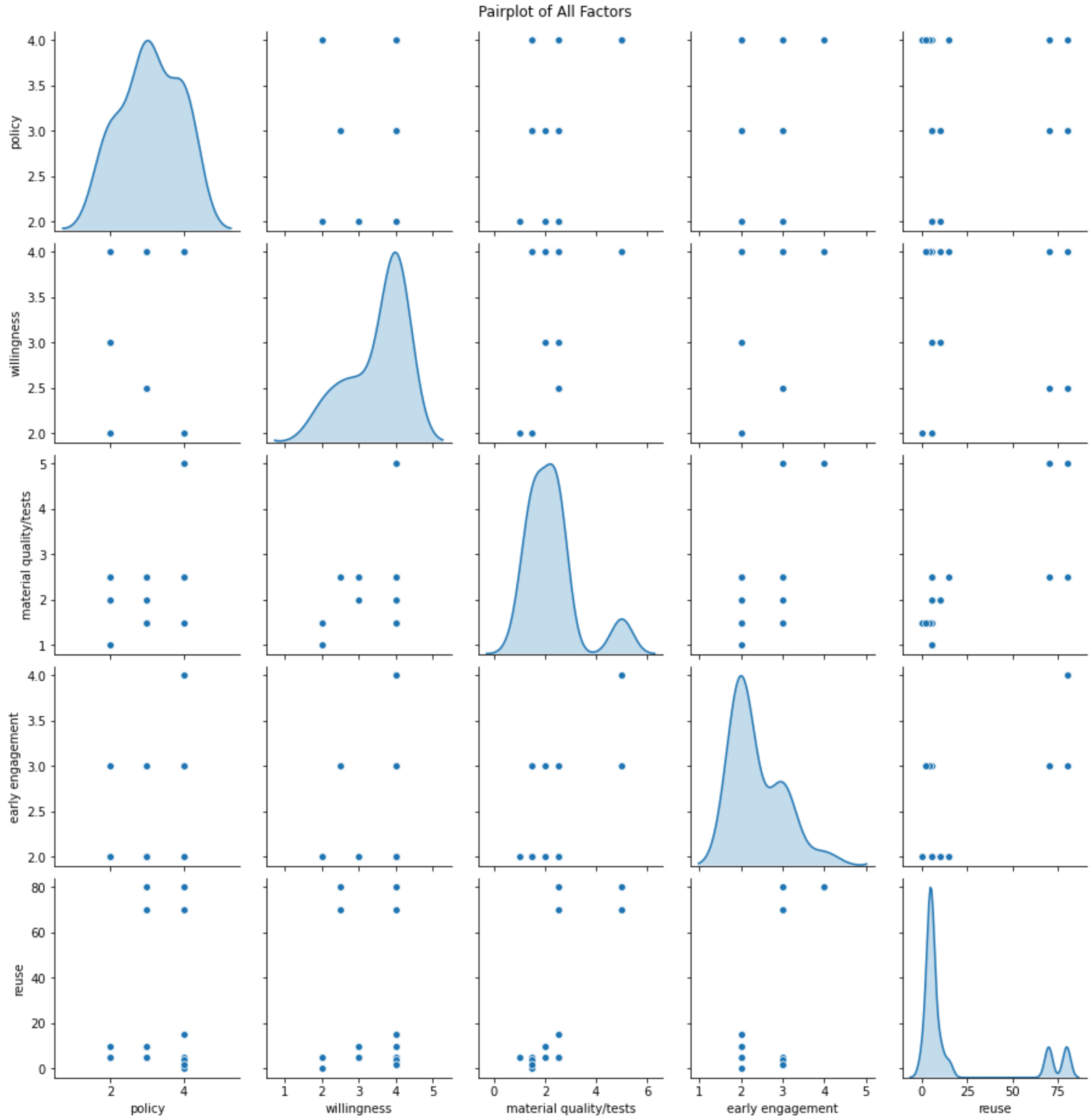
```
plt.tight_layout()
# Annotate each bar with its importance value
for bar, importance in zip(bars, feature_importances_gb):
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, yval + 0.01, f'{importanc
e:.2f}',
             ha='center', va='bottom', fontsize=10)


plt.show()


# Print model performance
print(f'Mean Squared Error (Gradient Boosting): {mae_gb:.4f}')
print(f'R-squared (Gradient Boosting): {r2_gb:.4f}')
```

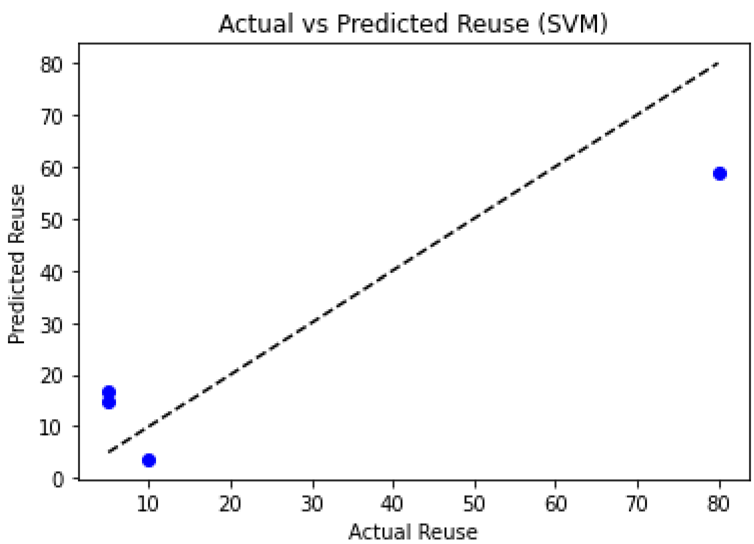





```
Mean Squared Error (Gradient Boosting): 5.3594
R-squared (Gradient Boosting): 0.9504
```

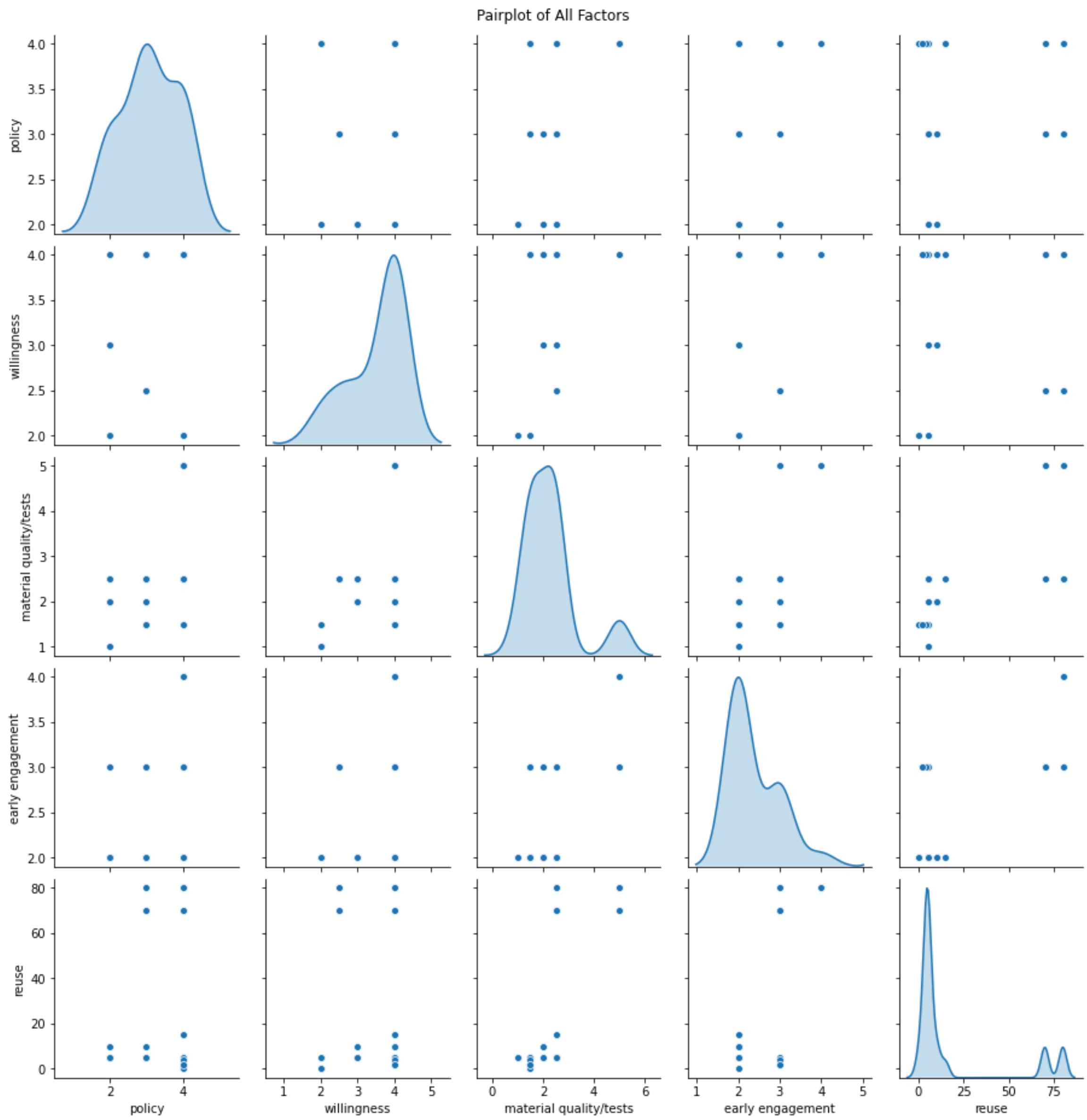
In [12]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score
import numpy as np


# Split the data into training and testing sets
X_train = df.iloc[4:21, :4]  # Features (Columns 1-4, Rows 5-20)
y_train = df.iloc[4:21, 4]   # Target (Column 5, Rows 5-20)

X_test = df.iloc[:4, :4]     # Features (Columns 1-4, Rows 1-4)
y_test = df.iloc[:4, 4]      # Target (Column 5, Rows 1-4)

# Train the Support Vector Machine model (SVR)
model_svr = SVR(kernel='rbf', C=100, epsilon=0.1)  # rbf kernel, you can ex
periment with other kernels
model_svr.fit(X_train, y_train)

# Make predictions on the test set
y_pred_svr = model_svr.predict(X_test)

# Calculate performance metrics
mse_svr = mean_squared_error(y_test, y_pred_svr)
r2_svr = r2_score(y_test, y_pred_svr)

# Visualizations
# Pairplot for all factors
sns.pairplot(df, diag_kind='kde')
plt.suptitle('Pairplot of All Factors', y=1.02)
plt.show()


# Scatter plot of predicted vs actual values
plt.scatter(y_test, y_pred_svr, color='blue')

# Calculate correct min and max values
min_val = min(y_test.min(), y_pred.min())
max_val = max(y_test.max(), y_pred.max())

# Plot the perfect prediction line
plt.plot([min_val, max_val], [min_val, max_val], '--k', label='Perfect Pred
iction')  # Ideal line
plt.xlabel('Actual Reuse')
plt.ylabel('Predicted Reuse')
plt.title('Actual vs Predicted Reuse (SVM)')
plt.show()

# Print model performance
print(f'Mean Squared Error (SVM): {mse_svr:.4f}')
print(f'R-squared (SVM): {r2_svr:.4f}')
```

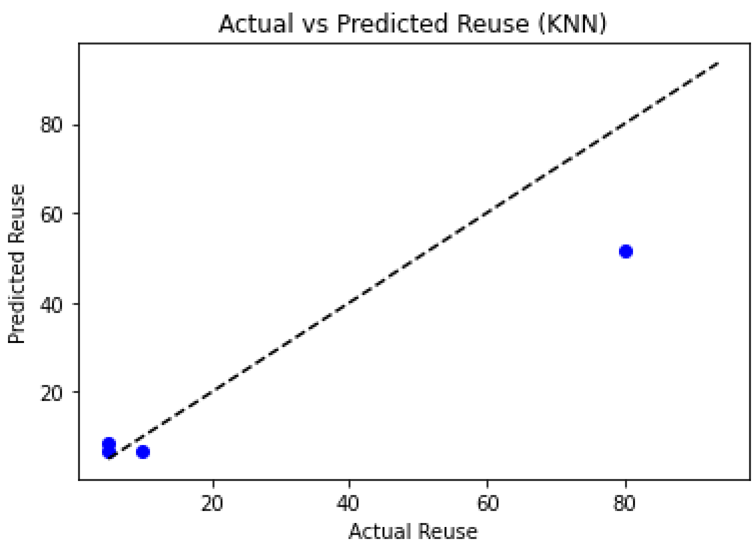





```
Mean Squared Error (SVM): 179.8180
R-squared (SVM): 0.8224
```

In [32]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error, r2_score


# Split the data into training and testing sets
X_train = df.iloc[4:21, :4]  # Features (Columns 1-4, Rows 5-20)
y_train = df.iloc[4:21, 4]   # Target (Column 5, Rows 5-20)

X_test = df.iloc[:4, :4]     # Features (Columns 1-4, Rows 1-4)
y_test = df.iloc[:4, 4]      # Target (Column 5, Rows 1-4)



# Train the KNN model
model_knn = KNeighborsRegressor(n_neighbors=3)  # You can experiment with d
ifferent numbers of neighbors
model_knn.fit(X_train, y_train)

# Make predictions on the test set
y_pred_knn = model_knn.predict(X_test)

# Calculate performance metrics
mae_knn = mean_absolute_error(y_test, y_pred_knn)
r2_knn = r2_score(y_test, y_pred_knn)

# Visualizations
# Pairplot for all factors
sns.pairplot(df, diag_kind='kde')
plt.suptitle('Pairplot of All Factors', y=1.02)
plt.show()


# Scatter plot of predicted vs actual values
plt.scatter(y_test, y_pred_knn, color='blue')

# Calculate correct min and max values
min_val = min(y_test.min(), y_pred.min())
max_val = max(y_test.max(), y_pred.max())

# Plot the perfect prediction line
plt.plot([min_val, max_val], [min_val, max_val], '--k', label='Perfect Pred
iction')
plt.xlabel('Actual Reuse')
plt.ylabel('Predicted Reuse')
plt.title('Actual vs Predicted Reuse (KNN)')
plt.show()

# Print model performance
print(f'Mean absolute Error (KNN): {mae_knn:.4f}')
print(f'R-squared (KNN): {r2_knn:.4f}')
```






```
Mean absolute Error (KNN): 9.1667
R-squared (KNN): 0.7956
```

In [ ]:

In [ ]:

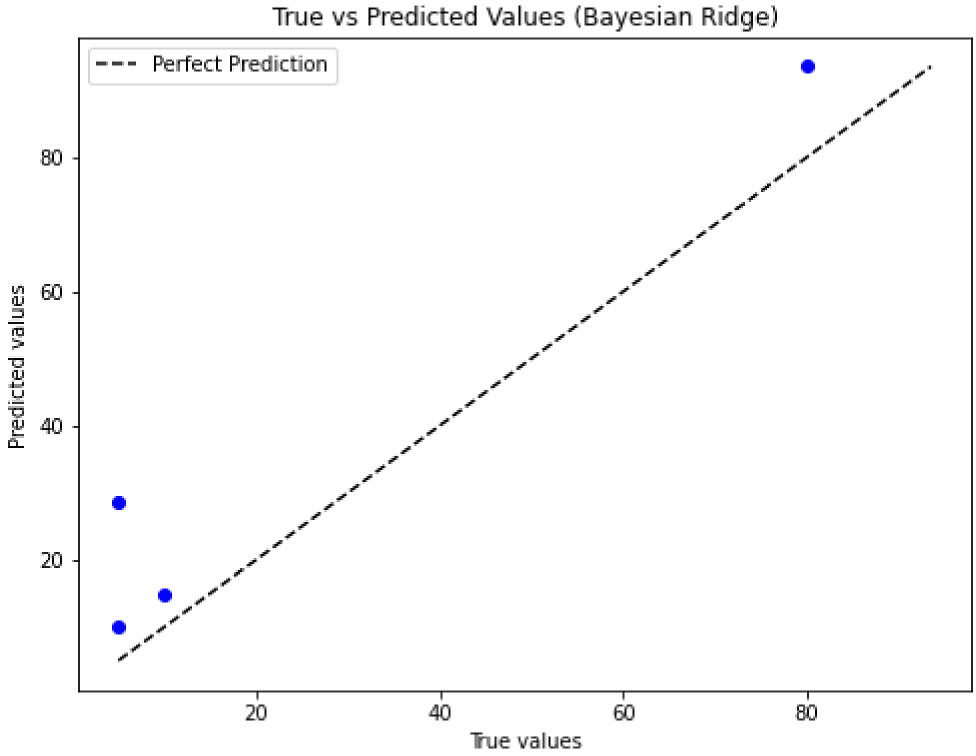
```
In [ ]:
```

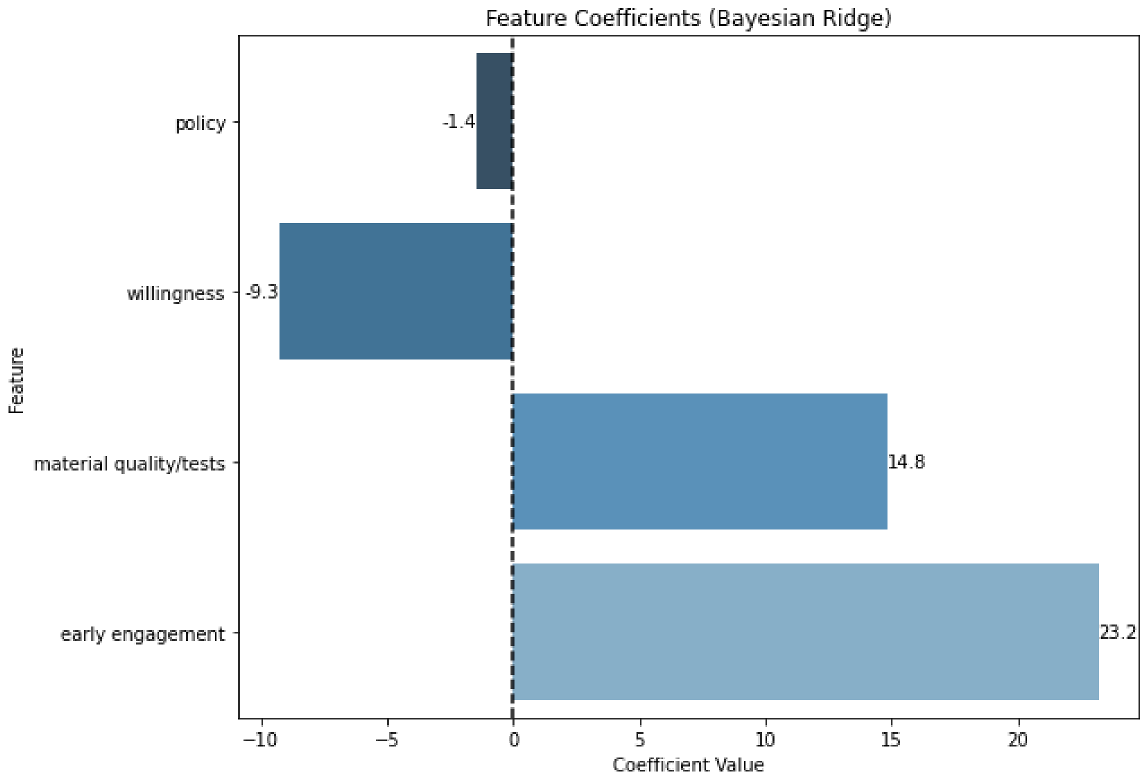
In [31]:

```
import pandas as pd
from sklearn.linear_model import BayesianRidge
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns


# Split the data into features (X) and target (y)


X_train = df.iloc[4:21, :4]  # Features (Columns 1-4, Rows 5-20)
y_train = df.iloc[4:21, 4]   # Target (Column 5, Rows 5-20)

X_test = df.iloc[:4, :4]     # Features (Columns 1-4, Rows 1-4)
y_test = df.iloc[:4, 4]      # Target (Column 5, Rows 1-4)

# Split the data into training and testing sets


# Train a Bayesian Ridge model
model = BayesianRidge()
model.fit(X_train, y_train)

# Predict on the test set
y_pred = model.predict(X_test)

# Evaluate the model
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print the evaluation results
print(f'Mean Absolute Error (Bayesian Ridge): {mae:.3f}')
print(f'R-squared (Bayesian Ridge): {r2:.4f}')

# Plotting the predictions vs true values
plt.figure(figsize=(8,6))
plt.scatter(y_test, y_pred, color='blue')

# Calculate correct min and max values
min_val = min(y_test.min(), y_pred.min())
max_val = max(y_test.max(), y_pred.max())

# Plot the perfect prediction line
plt.plot([min_val, max_val], [min_val, max_val], '--k', label='Perfect Pred
iction')

plt.xlabel('True values')
plt.ylabel('Predicted values')
plt.title('True vs Predicted Values (Bayesian Ridge)')
plt.legend()
plt.show()

coefficients = model.coef_
features = X_train.columns

#plotting feature coefficients

plt.figure(figsize=(9, 7))
ax = sns.barplot(x=coefficients, y=features, palette='Blues_d')
```

```python
plt.title('Feature Coefficients (Bayesian Ridge)')
plt.xlabel('Coefficient Value')
plt.ylabel('Feature')
plt.axvline(0, color='black', linestyle='--')

# Add coefficient values next to bars
for i, v in enumerate(coefficients):
    ax.text(v, i, f'{v:.1f}', color='black', va='center',
            ha='left' if v > 0 else 'right')

plt.show()
```

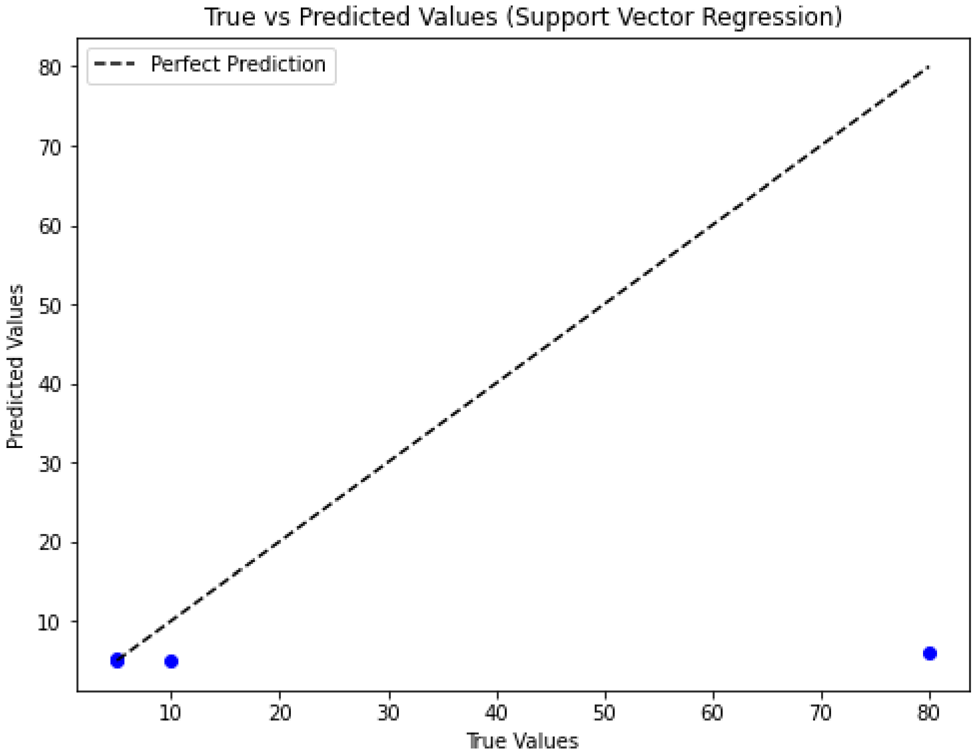
```
Mean Absolute Error (Bayesian Ridge): 11.807
R-squared (Bayesian Ridge): 0.8032
```



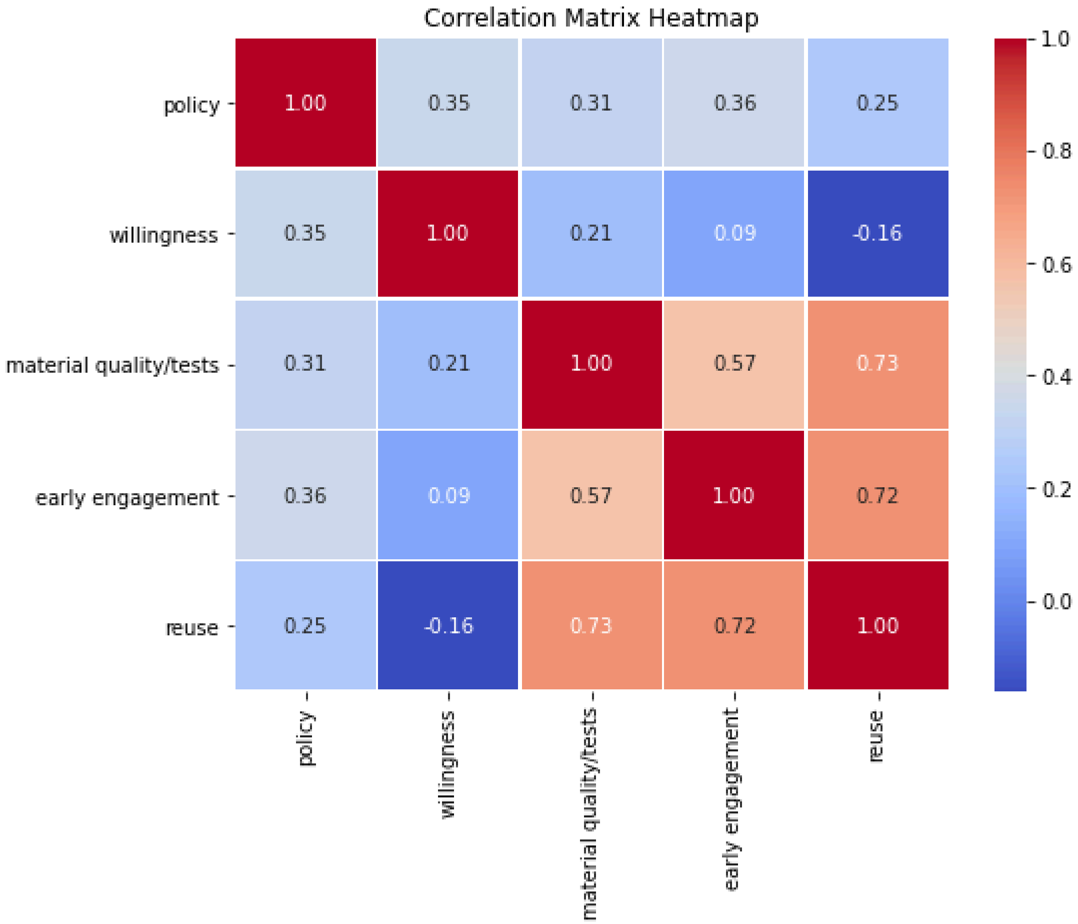


```
In [30]: import pandas as pd
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns


# Split the data into features (X) and target (y)
X = df[['policy', 'willingness', 'material quality/tests', 'early engagemen
t']]
y = df['reuse']

# Split the data into training and testing sets
X_train = df.iloc[4:21, :4]  # Features (Columns 1-4, Rows 5-20)
y_train = df.iloc[4:21, 4]   # Target (Column 5, Rows 5-20)

X_test = df.iloc[:4, :4]     # Features (Columns 1-4, Rows 1-4)
y_test = df.iloc[:4, 4]      # Target (Column 5, Rows 1-4)


# Initialize and train the SVR model
model = SVR(kernel='rbf')  # Using radial basis function kernel (non-linea
r)
model.fit(X_train, y_train)

# Predict on the test set
y_pred = model.predict(X_test)

# Evaluate the model
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print the evaluation results
print(f'MAE (SVR): {mae:.4f}')
print(f'R-squared (SVR): {r2:.4f}')

# Plotting the predictions vs true values
# Plotting the predictions vs true values
plt.figure(figsize=(8,6))
plt.scatter(y_test, y_pred, color='blue')

# Calculate correct min and max values
min_val = min(y_test.min(), y_pred.min())
max_val = max(y_test.max(), y_pred.max())

# Plot the perfect prediction line
plt.plot([min_val, max_val], [min_val, max_val], '--k', label='Perfect Pred
iction')

# Label and title
plt.xlabel('True Values')
plt.ylabel('Predicted Values')
plt.title('True vs Predicted Values (Support Vector Regression)')
plt.legend()
plt.show()
```

```
MAE (SVR): 19.7991
R-squared (SVR): -0.3571
```



In [16]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Select only columns 1 to 5 (Python uses 0-based indexing, so this means c
olumns with index 0 to 4)
numeric_df = df.iloc[:, 0:5]

# Compute correlation matrix
correlation_matrix = numeric_df.corr()

# Plot heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', lin
ewidths=0.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```



In [ ]: