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Stakeholders' impact on the reuse potential of structural elements at the end-of-life of a building: A machine learning approach

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ABSTRACT

The construction industry, and at its core the building sector, is the largest consumer of non-renewable resources, which produces the highest amount of waste and greenhouse gas emissions worldwide. Since most of the embodied energy and CO2 emissions during the construction and demolition phases of a building are related to its structure, measures to extend the service life of these components should be prioritised. This study develops a set of easy-to-understand instructions to facilitate the practitioners in assessing the social sustainability and responsibility of reusing the load-bearing structural components within the building sector. The results derived by developing and then employing advanced machine learning techniques indicate that the most significant social factor is the perception of the regulatory authorities. The second and third ranks among the social reusability factors belong to risks. Since there is a strong correlation between perception and risk, the potential risks associated with reusing structural elements affect the stakeholders' perception of reuse. The Bayesian network developed in this study unveil the complex and non-linear correlation between variables, which means none of the factors could alone determine the reusability of an element. This paper shows that by using the basics of probability theory and combining them with advanced supervised machine learning techniques, it is possible to develop tools that reliably estimate the social reusability of these elements based on influencing variables. Therefore, the authors propose using the developed approach in this study to promote materials' circularity in different construction industry sub-sectors.

1. Introduction

The construction industry is the backbone of the economic growth of many countries worldwide. With a global value of $11.6 trillion by 2030 and a Gross Domestic Product (GDP) of up to 10.5% in European countries [1], it employs nearly 7.8% of the total labour force in the UK [2–4]. However, this considerable contribution to the global economy makes this sector a leader in undesirable areas such as non-renewable resources consumption, waste and greenhouse gas (GHG) emissions production [5–12]. Therefore, it is inevitable to take efficient measures to improve the overall sustainability of the construction sector to maintain the rise of the global temperature below 2 °C and comply with the requirements of the Paris agreement and COP27 [13]. According to the signatories of the Paris Agreement, one subsidiary of the construction industry that has a high potential to take part in this venture is the building

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sector [14,15]. More specifically, since most of the embodied energy and CO2 emissions during the construction and demolition phases are related to the structure of a building, measures to extend the service life of these components should be prioritised [16].

Waste hierarchies identify prevention and reuse as the most effective solution to improve material efficiency in all economic sectors, including the building industry [17,18]. New design methods such as design for deconstruction (DfD) have the potential to decrease waste (the first option according to the waste hierarchies) and promote the reusability of the structural elements in new buildings [19,20]. Whereas, due to the lack of such features in the existing buildings, reuse remains the best solution for addressing the negative environmental impacts of construction and demolition activities. Nevertheless, low reuse rates and declining trends in reusing structural elements of buildings show that other less efficient waste treatment methods such as recycling are being practised widely [9,21,22].

In recent years, estimating the reusability of the structural elements of a building has been identified as a solution to promote reuse in the building sector. Therefore, several studies focused on developing tools to identifying the mechanical properties of these components to estimate their reusability [23–28] (please refer to Ref. [29] for a brief discussion on these papers). However, these studies overlooked the impact of significant social and economic factors identified as reuse barriers in the literature [30].

In brief, the deficiencies of the methods used to evaluate or predict the reusability of load-bearing building elements include.

i. Most of these methods are focused on one aspect of reusability, which is determining the mechanical properties of the elements.
ii. They are limited to a specific material.
iii. They do not consider the economic and social reusability of the elements (as essential dimensions of sustainability).
iv. Most of them are not based on real projects with reused structural components.
v. The complexity of the interactions of the affecting variables is ignored.
vi. None of these studies used advanced data analysis methods such as novel/advanced supervised machine learning techniques to reveal the sophisticated relationship between the variables and then predict the reusability of the elements using the developed probabilistic models.

The environmental advantages of reusing the load-bearing structural components make this intervention a sustainable solution to address the negative impacts of the construction and demolition activities [30]. However, the integration of the recovered structural components into the design of a new building highly depends on the perceived risks and willingness of the key stakeholders such as clients and contractors [30]. While the systematic literature review performed by Rakhshan et al. [30] show the importance of social factors on the widespread reuse of the structural elements, none of the reviewed papers provides an indication of the social reusability of these components based on the identified barriers. Table 1 lists the papers identified during the systematic literature review, which were used to uncover the social drivers and barriers to reuse (i.e., the reusability factors). These variables were then used to develop the questionnaire survey used in this study.

This study intends to address the above gap by developing an efficient data-driven model to predict social sustainability due to the reusability of the structural elements. To avoid the use of convoluted language, hereafter, we will use “social reusability” instead of “social sustainability due to reusability”. For this purpose, the authors developed an online questionnaire to assess the factors affecting the reuse of the structural elements of a building based on the experts' opinions. Based on the results of the survey, the authors developed a set of predictive models using supervised machine learning techniques in ‘R’ (version 4.2.2) [56] to estimate the social reusability of the structural elements of a building. They then selected the best performing model and extracted easy-to-understand instructions to facilitate the practitioners in assessing the social reusability of the load-bearing structural components. This study is part of a broader research focused on developing tools to predict the technical, economic, and social reusability of the structural components of a building. The current paper addresses the social aspect of reusability, which is defined as the acceptance level of the stakeholders (clients, CEO, designers, construction team, occupants, etc.) about using the reused structural elements in the new building. For the technical and economic aspects of this research, please refer to Refs. [29,57], respectively.

The paper continues with the research method (Section 2), results and discussions (Section 3), and the conclusion (Section 4). The research methodology developed in this paper is presented in Fig. 1.

2. Method and data collection

This study intends to develop a tool to predict the social reusability of the structural elements of a building. For this purpose, the authors designed an online questionnaire based on the results of an earlier systematic literature review [30] and distributed the survey among professionals with experience in reusing building structural elements to assess the reusability factors.

The independent variables (features) in the questionnaire are the factors affecting the reuse of a structural component of a building, and the dependent variable (response) is the social reusability of the element. All questions in this questionnaire (features and response) are in the form of closed questions with a Likert scale varying from one to five [58]. A copy of the questionnaire is available in Appendix A. It should be noted that the available questionnaire in Appendix A is a part of a broader survey that is designed to assess the technical, economic, and social aspects of the reuse of the structural elements of a building. Since this paper only deals with the social dimension, irrelevant questions are removed to prevent confusion.

Section A of the questionnaire contains demographic questions and investigates the previous background of the respondent. This section helped the authors to make sure that the respondent matched the requirements of the study. Section B contains questions about the structural element that the respondent reused in the past and referred to it to complete the rest of the questionnaire. These questions are not used to develop the predictive models because they do not deal with the focus of this paper. Section C contains two questions and deals with the barriers to reuse, as identified in the literature. Section D contains reusability factors that can work as

Table 1
Reuse drivers and barriers identified during the systematic literature review.

Reviewed articles	Feature type (driver/ barrier)	Sub-category	Feature
[31]	Driver	Awareness	Increased awareness by recognition of reuse in the public debate
[32,33]	Driver	Awareness	Increased awareness of the full benefits of reuse among the stakeholders
[34]	Driver	Perception	Positive perception of contractors about reuse
[35]	Driver	Sustainability	Impact of society's environmental concerns
[36–38]	Driver	Trust	Informality and good relationship among the stakeholders can enhance reuse
[22,36,39–43]	Driver	Willingness	Client willingness to integrate reused elements
[34,38,39,42,44]	Driver	Willingness	Contractor willingness to integrate reused elements
[39,40,42,43,45,46]	Driver	Willingness	Design team willingness to integrate reused elements
[31]	Driver	Willingness	Unique appearance of reused elements
[46,47]	Barrier	Awareness	Lack of awareness about reused elements across the supply chain
[38,45]	Barrier	Awareness	Lack of awareness about the deconstruction risks and challenges
[38,45,48]	Barrier	Awareness	Lack of awareness of the full benefits of deconstruction among the stakeholders
[38,40,49]	Barrier	Awareness	Lack of awareness of the full benefits of reuse among the stakeholders
[40]	Barrier	Perception	Demolition is preferred to deconstruction due to the perceived economic and scheduling reasons.
[36,40]	Barrier	Perception	Negative perception of contractors about reused elements
[37,42,48,50]	Barrier	Perception	Negative perception of the clients about reused elements
[40]	Barrier	Perception	Negative perception of the designers about reuse
[32,35,42,45,46,48,49,51, 52]	Barrier	Perception	Negative perception of the stakeholders about reused elements
[48]	Barrier	Perception	Negative perception of the supervisors about reused elements
[46,53]	Barrier	Perception	Reused structural elements are not visually attractive
[43]	Barrier	Risk	Inequality in the distribution of risk among the stakeholders
[35,43,54]	Barrier	Risk	Lack of confidence in the quality of reused components
[37]	Barrier	Risk	Liability risk due to informality and trust
[45,49,51]	Barrier	Risk	Potential health and safety risks
[36,40,42,45,46,48]	Barrier	Risk	Risks associated with reuse (liability, fear, etc.)
[51,55]	Barrier	Sustainability	Unsatisfactory working environment during the treatment of the reused elements
[42,43]	Barrier	Trust	Lack of trust to the supplier of reused elements
[31,40,45,46,53]	Barrier	Willingness	Construction sector inertia/resistance against reuse
[40]	Barrier	Willingness	Contractors' unwillingness to work with the reused element
[45,48]	Barrier	Willingness	Design team unwillingness to integrate reused elements
[45,46,49,50]	Barrier	Willingness	Lack of client demand/support
[38,45]	Barrier	Willingness	Lack of interest to integrate reused materials in the projects
[48]	Barrier	Willingness	Regulatory authority unwillingness to integrate reused elements

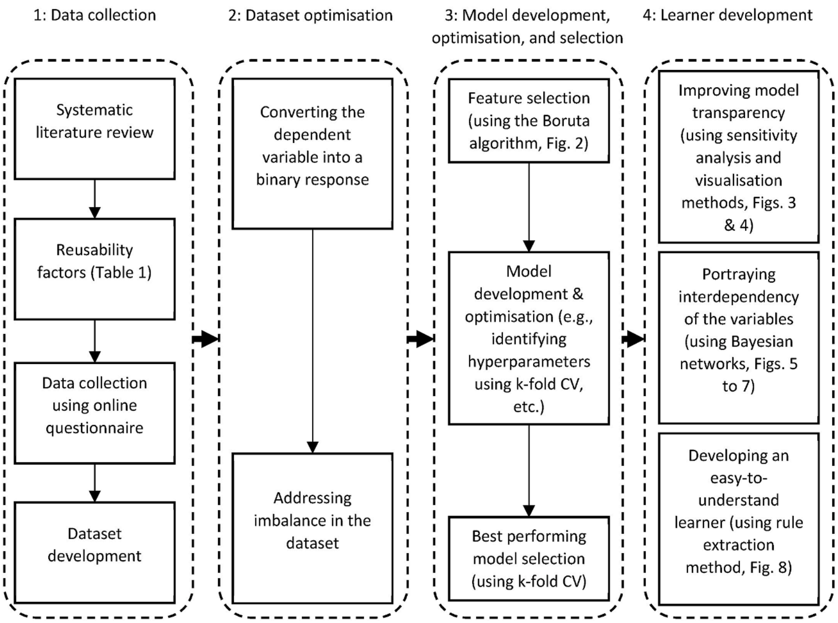

Fig. 1. Research methodology used in this study.

reuse barriers or drivers in different circumstances. For instance, the perception of a client can be in favour of reuse or against it. And Section E of the survey contains the dependent variable. The respondents were inquired to provide their judgement on the social reusability of the component. Table 2 provides the list of the features and the response used in this research.

In this study, all the experts are located using the companies' websites and LinkedIn. While a company's website gives a general overview of the top management team and the types of services the company offers (which depends on their privacy policy), it does not provide any details about the employees recruited by the company. On the other hand, LinkedIn provides a platform for accessing the professionals and their profiles and level of experiences at no cost. According to Ref. [59], LinkedIn is "the most important cross-industry professional network around" with more than 645 million members from 200 countries worldwide [60] and a high growth rate in the number of experts joining this social media [61]. After the sampling frame was developed, all the located experts were contacted. As a result, a total number of 481 invitations were sent to the experts to complete the online questionnaire, and 90 completed questionnaires were received, resulting in a response rate of 18.7%. After careful review of the responses, 18 questionnaires disqualified due to either being irrelevant to the focus of the study or being incomplete. Based on the above, 72 questionnaires are used for statistical analysis and predictive model development in this research.

This study investigates the impact of various factors on the reusability of the structural elements of a building. Therefore, a respondent may need to refer to different documents to answer the questions on the questionnaire. A self-administrated questionnaire, as used in this study, is very efficient because the respondent can spend enough time answering each question and complete the survey at a later time [62]. Before developing the predictive models, the authors performed a reliability analysis to assess the quality of the collected data. Reliable research needs to be reproducible by other researchers. This applies to all aspects of research, including data collection. In a questionnaire survey, this is guaranteed by making sure that the respondents represent the target population. One indicator of the reliability of the collected data is the response rate. However, according to Ref. [61], if the sample represents a population, it is possible to have reliable data with a low response rate. In this study, the authors requested all located experts with previous experience in structural elements reuse to complete the survey. Therefore, the quality of data is expected to be high as the questionnaires were completed by the experts. Likewise, at the beginning of the questionnaire, the respondents were asked to confirm if they had previous practical experience reusing buildings' structural elements. All respondents confirmed they have such experience. Therefore, they represent the population of reuse experts. It should be noted that the experts' opinions play an import role in acquiring invaluable information, when the problem under study is a new real-world challenge or the available data is limited [63].

Furthermore, the authors calculated Cronbach's alpha value of the received responses as an essential indication of the reliability of the questionnaire survey [64]. For this purpose, the authors used SPSS 25 to calculate the Cronbach's alpha values of the survey. If the Cronbach's alpha value of a set of questions is more than 0.7, then these questions measure the same thing, and the answers are reliable [64]. The results of the reliability analysis of the collected data are available in Appendix B. According to the reliability analysis, the Cronbach's alpha values of Sections C & D (the independent variables) are more than 0.8, which means that the collected data are reliable.

3. Results and discussion

The questionnaire survey helped to quantify the qualitative factors affecting the reusability of the structural elements of a building (Section 3.1). The authors then used these quantitative data to develop a set of models to assess and predict the social reusability of these components using advanced machine learning techniques (Section 3.2). After selecting the best-performing model, to enable the practitioners to use the results of the predictive model effectively, a set of easy-to-understand rules will be developed and discussed (Section 3.3).

3.1. Preliminary analysis of the survey

In this section, descriptive statistics, including measures of central tendency (mean, median, mode, etc.) and measures of variability (standard deviation, variance, minimum/maximum, skewness, etc.) are used to get the initial insights into the factors affecting the reusability of the structural elements of a building and rank them based on their mean values.

Table 2
The features and the response.

Variable code	Variable description	Variable category
C22	The potential liability risk	Feature
C23	The potential health & safety risks	Feature
D11	Perception of the client/top management	Feature
D12	Perception of the designers	Feature
D13	Perception of the builders/contractors	Feature
D14	Perception of the end-users (when it is not the client)	Feature
D15	Perception of the stockist	Feature
D16	Perception of the regulatory authorities	Feature
D17	Visual appearance	Feature
D20	Changes in the health & safety regulations	Feature
E3	Social reusability of the element	Response

The results of the descriptive statistics are presented in Appendix B and briefly discussed in this section. While, according to Ref. [65], the permissible statistics for ordinal scales are the median and percentiles, the interval and ratio scales for ordinal values, such as Likert scales, are mostly recommended in other studies [66], and also found to be more plausible to be used in this research.

The results of the descriptive statistics of the received questionnaires revealed that the following barriers significantly affect the social reusability of the load-bearing building components (Appendix B). The following ranking is based on the mean value of the variables in Appendix B, Section D. A lower mean value (μ) is interpreted as the tendency of the factor to act as a barrier against reuse.

- Changes in the health and safety regulations (fire, etc.) ($\mu = 2.65$) (D20)
- Perception of the stockist about the element ($\mu = 2.71$) (D15)
- Perception of the regulatory authorities about the element ($\mu = 2.97$) (D16)
- Perception of the builders/contractors about the element ($\mu = 3.1$) (D13)

According to these variables, the perception of the stakeholders has the highest impact on the social reusability of the load-bearing building components.

While the results of the descriptive statistics provide an overview of the barriers to reuse from different perspectives, it should be noted that these variables cannot be directly used to determine if a structural component is reusable or not. For instance, as discussed above, changes in the health and safety regulations (fire, etc.) (D20) is the most significant barrier with a mean value of 2.65 and a standard deviation of 0.981 (Appendix B). Considering D20, to decide if an element is socially reusable or not, a model predicts reusable if $D20 \geq 3$, which results in predicting 51 reusable and 21 non-reusable components (Table 3). The following confusion matrix (Table 3) is developed based on this classifier for the entire dataset (72 responses). As can be observed, the model's overall accuracy is equal to 54% (39 correct predictions divided by 72 valid responses). On the other hand, since the number of reusable components in the received dataset is 56, a baseline model will always predict reusability for all elements, which results in an overall accuracy of 77% for such a simple model. The accuracy of the baseline model shows that using the $D20 \geq 3$ rule as an indication of reusability results in a prediction worse than the baseline model, which is not acceptable. Please note that a baseline model is a model that assigns the most frequent response as its prediction for all observations in a classification problem, such as being reusable (1) or non-reusable (0).

Moreover, the results of the descriptive statistics do not reveal which combination of variables could provide the most accurate estimate of the reusability of a component. In this research, these shortcomings are addressed in Sections 3.2 and 3.3.

3.2. Developing the best-practice predictive model

Before developing the predictive models, the authors converted the dependent variable (question E3 in the questionnaire) into a binary response with zero (0) indicating non-reusable and one (1) reusable. The decision for this conversion was made due to the aim of the study, which is predicting if a structural element at the end-of-life of a building is socially reusable or not. For this purpose, following a similar approach adopted by Ref. [67], responses with Likert scale values 1 to 3 were considered non-reusable, and the remaining scales (4 and 5) reusable.

While the above conversion complies with the aim of this paper, converting the multi-scale response (question E3) into a binary one has several other advantages too. Firstly, the practitioners who wish to use the results of this study do not need to make a judgement about the reusability of a component based on a five-scale variable. Moreover, supervised machine learning techniques require a considerable number of observations to make reliable predictions with a multi-scale response. However, since the reuse of the load-bearing structural components of buildings is not a widespread practice, and, in fact, in places like the UK, it has been declining during the last decades [21,22], the number of available experts with the desired profile in this field is limited. On the other hand, a binary response does not need a large dataset. Likewise, quantifying the response is based on the expert opinion of the practitioners, which might suffer from a level of uncertainty. This fact makes the analysis of a multi-scale dependent variable inappropriate for the collected data in this study. Whereas a binary response is less affected by this uncertainty and the small size dataset.

3.2.1. Oversampling for imbalance classification problem

After converting the multi-scale response into zero (0) and one (1), we observed that the resulting dataset suffers from a considerable imbalance with 23% non-reusable and 77% reusable observations. This imbalance in the dataset decreases the reliability of the predictions made by the models and should be addresses properly [68–70]. It is because when one class is dominant (due to the imbalance in the dataset), the predictions are inherently biased towards that class, yielding an unrealistic accuracy [68]. One solution to overcome this situation is by collecting more data. However, as discussed earlier, due to the low rates of reusing the structural elements in the building sector, this option was not practical. Moreover, since the respondents were free to choose any structural element with any level of reusability to complete the online questionnaire, the resulting dataset could still suffer from the observed imbalance.

Table 3
Social reusability of the elements in the original dataset using the $D20 \geq 3$ rule only.

	Predicted response values	
	Non-reusable (0)	Reusable (1)
Actual non-reusable (0)	2	14
Actual reusable (1)	19	37

In supervised machine learning, different methods can be used to address the issues caused by an imbalanced dataset [69,70]. These include cost-sensitive learning (manipulating the threshold values, etc.), pre-processing the imbalanced dataset (oversampling, under-sampling, SMOTE, etc.), algorithm level approaches (active learning, kernel modifications, etc.), and ensemble learning (cost-sensitive boosting, etc.) [70]. It should be noted that according to Ref. [70], there is no best strategy to deal with the issues caused by imbalanced datasets.

In this study, the authors used the Synthetic Minority Oversampling Technique (SMOTE) to overcome the imbalance in the dataset [71]. The advantage of this technique over other oversampling methods is that it decreases the imbalance in a dataset by synthetically creating new examples of the minority class, and not duplicating them [71,72]. It should be noted that following [73–76], the SMOTE technique on the entire dataset was applied, which resulted in a new dataset with 112 observations. After performing SMOTE, the imbalance in the dataset improved from 23% (non-reusable) and 77% (reusable) to 53% (non-reusable) and 47% (reusable). While the baseline dataset with 72 acceptable responses satisfies the minimum required ratio of 5 observations for each independent variable to have a generalisable and unbiased multivariate data analysis, as advised by Ref. [77], using SMOTE further strengthens the reliability of the research findings.

3.2.2. Feature selection

One essential stage in the development of predictive models, using supervised machine learning techniques, is the selection of relevant features [68]. One might argue that the independent variables (features) used in the questionnaire survey are all relevant. However, there is a chance that some variables are highly correlated or irrelevant, and their presence negatively affects the performance of the model. Therefore, it is essential to use advanced machine learning tools to identify the irrelevant and redundant features in a dataset and not use them during the development of the predictive models [78].

In this study, the Boruta method is used to perform feature selection [79]. This method is a backward feature elimination wrapper and uses an all-relevant feature selection method, which minimises the random selection of variables [79,80].

The Boruta package performs variable selection using the "RandomForest" package in R [79,81]. This package assesses the importance of the independent variables of a dataset using the permutation accuracy importance measure [79,82]. In the first stage, the Boruta method enhances the dataset by introducing a copy of the reusability factors. Next, the Boruta method creates shadow features by eliminating the correlation of the copied independent variables with the response (question E3) by randomly changing their values. Then, the random forest method gathers the Z-statistics of the extended dataset. It identifies the shadow feature with maximum Z-statistic (known as the Maximum Z-statistic Shadow Feature or MZSF). The method then gives a hit to an independent variable (the features in the original dataset) with a z-score higher than MZSF. For undecided variables, a two-tailed test of equal variance is performed with the MZSF. Variables with z-scores significantly higher or lower than MZSF are important (Confirmed) or unimportant (Rejected), respectively. However, if the method is unable to decide, the feature will be reported as Tentative. In this case, the researcher can either increase the number of iterations or decide to include or exclude a feature based on expert opinion.

Analysing the results of variable selection (Fig. 2) reveals that all the features are necessary. Therefore, all predictors listed in Sections C & D of the questionnaire (Appendix A) will be considered for developing the predictive models in Section 3.2.3.

3.2.3. Model development

According to the 'no free lunch' theorem, there is no single supervised machine learning method suitable for all types of datasets [83]. Therefore, choosing an optimum model that has a high performance and makes minimum classification errors is challenging [84]. Moreover, since the goal of this study is to improve the reuse rates by assisting the practitioners in their decisions making process, the resulting model must be easily interpretable, as well.

In this study, thirteen different machine learning methods were used to develop a wide range of predictive models. The selected methods vary from simple logistic regression (parametric and easily interpretable) to support vector machines (non-parametric and hard to interpret to the practitioners). This study intends to develop an easy-to-understand predictive model that estimates the social

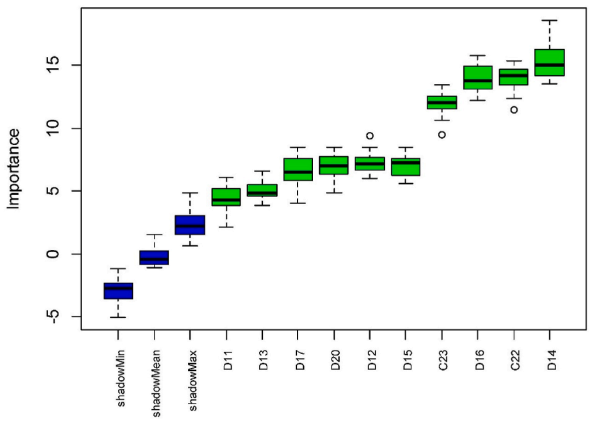

Fig. 2. Importance of the features in the dataset using the Boruta method.

reusability of the structural components of a building. Therefore, it seems reasonable to only develop interpretable models. However, since most of these methods consider a functional form for the relationship between the predictors and the response, the resulting predictions can be highly biased [84]. On the other hand, the non-parametric and complex methods such as the SVM and KNN (Table 4) result in very accurate predictions on the training data [84–86]. However, since these methods can be highly flexible, they might accurately follow the training observations, resulting in highly overfitted models that suffer from high variance [84]. It means that they might make many misclassifications on new observations, which have not been seen during the training process. Therefore, in selecting the machine learning methods to develop the predictive models, the authors considered this bias-variance trade-off to be able to choose the best performing model [86–88].

3.2.4. Selecting the best classifier

There are two methods to develop a predictive model and estimate its performance. The first option is to use the entire dataset to develop a model and then collect new observations and test its performance. However, this approach is not very practical because of time-constraints to collect new data as well as limitations such as limited reuse rates, which makes the task of finding experts in this field challenging (Section 3.2). The second option, which is widely used in supervised machine learning, is splitting the dataset into training and testing observations. In this approach, the researcher uses the training observations to develop a model, and then uses the testing data (unseen to the classifier) to evaluate its performance. There are three ways to use the available dataset to train and test a predictive model. These are the validation set approach, k-fold Cross-Validation (kfCV), and Leave-One-Out Cross-Validation (LOOCV) [84].

In this study, the authors used the kfCV ($k = 10$) to develop predictive models and evaluate their performances [84]. This approach has several advantages to the other two methods. In the validation set approach, a dataset is randomly divided into testing and training sets with a ratio varies from 50/50 to 80/20 (80% to develop the model and 20% to assess the performance). However, this approach could suffer from high variance because if it is repeated, due to the random nature of the division, the resulting predictions might be different. In the LOOCV method, this technique could result in highly accurate predictions on the training observations. However, it suffers from a higher variance than the kfCV method. Whereas the kfCV method with k equal to 5 or 10 have empirically shown to be resistant to both high bias and variance [84].

In the kfCV method, initially, the dataset is randomly divided into k folds, and a supervised machine learning method uses k-1 folds to train the classifier and the remaining fold to test its performance. This process continues k times until all folds are once used to test the performance of the model. The final test performance of the classifier is the average performance of the k folds [84].

In this study, the authors considered three metrics to compare the performance of the developed models. The first metric is the Type-I error rate. The type-I error rate is defined as the number of non-reusable components misclassified as reusable divided by the total non-reusable elements in the test dataset. The second metric is the overall accuracy of the classifier, which is equal to the total number of misclassifications divided by the total number of observations in the test set. And the third metric is the Area Under the, Receiver Operating Characteristic (ROC), Curve (AUC) [84]. These metrics are computed for the different classifiers and illustrated in Table 4.

The authors considered the following threshold values for these metrics to compare the performance of the classifiers and choose the best classifier. For the Type-I error rate, this threshold has a maximum value of 10%. For the overall accuracy and the AUC, minimum values of 85% and 90% are considered, respectively. By referring to these values, it can be observed that none of the interpretable models fulfils these performance requirements (Table 4). Hence, the authors decided to select the best performing model purely based on these three metrics and not its interpretability. Accordingly, the random forest (RF) model, which outperforms all

Table 4
Mean values of the metrics used to assess the performance of the various classifiers (10-fold CV method).

Model	Parametric/Non-parametric	Interpretable	Type I error	Overall accuracy	AUC
K-Nearest Neighbours (KNN)[a]	Non-parametric	No	0.03	0.81	0.92
Logistic Regression (LR)	Parametric	Yes	0.26	0.70	0.85
Linear Discriminant Analysis (LDA)	Parametric	Yes	0.25	0.72	0.85
Quadratic Discriminant Analysis (QDA)	Parametric	No	0.28	0.76	0.91
Naïve Bayes (NB)	Parametric	No	0.14	0.80	0.86
Decision Trees (DT)	Non-parametric	Yes	0.16	0.77	0.87
Random Forests (RF)[b]	Non-parametric	No	**0.00**	**0.94**	**0.96**
Adaptive Boosting (AB)	Non-parametric	No	0.07	0.81	0.91
BART Machine (BM)	Non-parametric	No	0.04	0.82	0.91
Artificial Neural Networks (single-layer perceptron) (ANN)[c]	Parametric	No	0.10	0.80	0.84
Gaussian Processes (GP)	Non-parametric	No	0.03	0.81	0.92
Propositional Rule Learner (PRL)	Non-parametric	Yes	0.04	0.85	0.88
Support Vector Machine (SVM)[d]	Non-parametric	No	0.10	0.87	0.94

Hyperparameters (calculated using 70% of the dataset that was selected randomly).
[a] $k = 8$.
[b] $ntree = 500, mtry = 3, nodesize = 1$.
[c] $Size = 8, Decay = 0.04$.
[d] $Cost = 1.45e9, Sigma = 0.366348636$.

other models, is selected as the best-practice model, or classifier, for assessing the social reusability of the structural components of a building.

It should be noted that, as described in Appendix D of the technical aspect of this research [29] and mentioned in the footnote of Table 4, KNN, RF, ANN, and SVM use hyperparameters, which were set before developing the models. Please refer to Appendix D of our technical reusability paper [29] for further details about each model and how the hyperparameters were set. Also, for further details about encoding the hyperparameters, please refer to Section 3.2.2 of [86]. Likewise, the R codes for all models developed by the corresponding author are available in Appendix E of [89].

3.3. Mining the selected RF model

The RF model selected in Section 3.2.4 is a black-box model, which means it is not very straightforward to interpret [90]. Therefore, in this section, two methods are used to improve its transparency. The first method helps in opening this black-box model by identifying the relative importance of the features using sensitivity analysis (SA) and visualisation techniques suggested by Ref. [85] (Section 3.3.1). The second method uses the results of the first technique and, following the approach suggested by Ref. [91], develops an easy-to-understand set of rules that can be used by practitioners to evaluate the social reusability of the structural elements (Section 3.3.2).

3.3.1. Improving the transparency of the selected RF model

Cortez and Embrechts [85] developed a SA and visualisation method to open any black-box model, including the RF model. The technique suggested by Ref. [85] requires a sensitivity method to change the values of an independent variable from its minimum to maximum values to assess the impact of this change on the dependent variable (called sensitivity responses). During this process, the values of other variables are not altered.

They then developed this method further and created a data-based sensitivity analysis (DSA), which is mainly used in this paper as the SA measure. The DSA draws several samples from the original dataset at random. Then, the DSA changes the value of an independent variable in the samples and records the impact of this change on the resulting response, while maintaining the conditions of other predictors. This process continues for all features. Next, this technique uses a sensitivity measure to identify the relative importance of the features using the recorded sensitivity responses. This paper uses the Average Absolute Deviation (AAD) from the Median as one of the DSA methods, which is more suitable for the type of categorical data used in this paper [85]. This method ranks the features based on the value of the AAD from the highest (most significant) to the lowest (least important). In this paper, the authors used the entire dataset to perform the SA and visualisation, as recommended by Ref. [85].

Fig. 3 presents the result of the feature importance by adopting the AAD method. According to this figure, all variables have relative importance above 0.02 and are necessary. This observation is in line with the results of feature selection using the Boruta technique (Section 3.2.2). Therefore, all the predictors in Figs. 1 and 2 will be used to develop an easy-to-understand learner in Section 3.3.2.

In the next stage, a set of variable effect characteristic (VEC) curves is plotted for the top-four features to present the impact of different values of these predictors on the social reusability of the structural elements of a building.

Fig. 4 shows the SA of the top-four features. For D16, C22, and D15, the higher values of the variables are associated with an improvement in social reusability. Whereas for C23, this increase has a counter effect. Notwithstanding, this variable cannot determine the social reusability of a component on its own, and the interactions with other variables should be considered, as well. For instance, according to Table 5, C23 is positively correlated with C22 and has a negative correlation with all other variables. While Table 5 clearly shows the interdependencies among the variables, it does not mean that the real relationship between predictors is linear. The

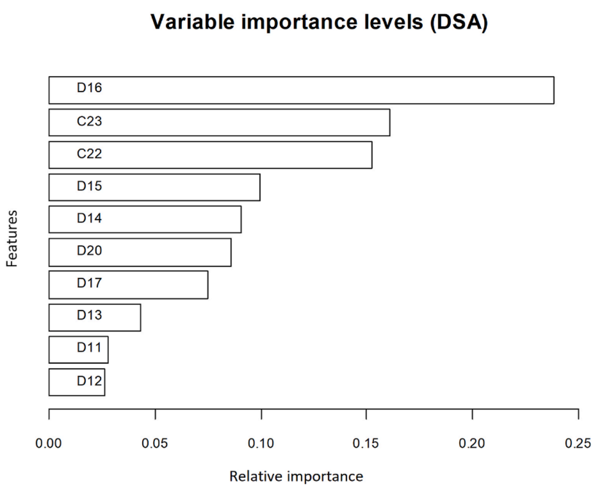

Fig. 3. Bar plot of the AAD relative feature importance (as the most suitable DSA) based on the selected RF model.

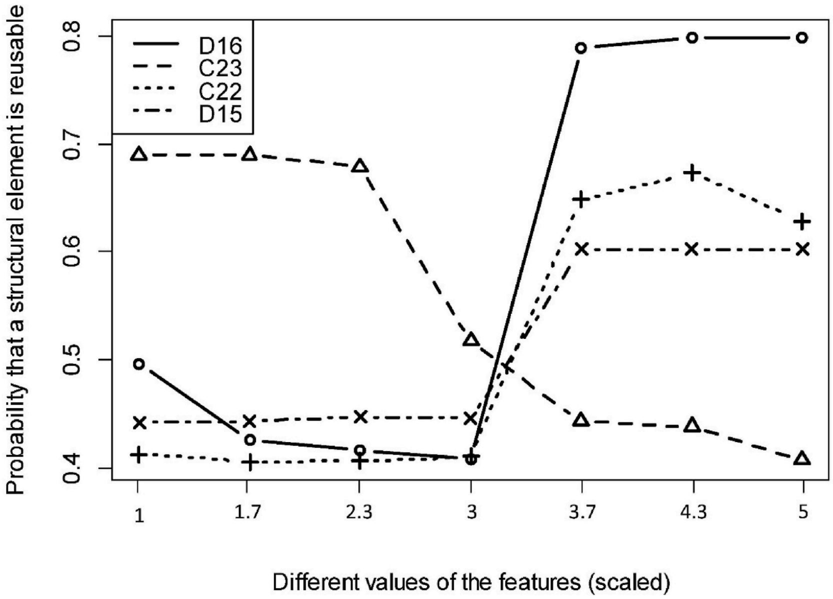

Fig. 4. The impact different values the features on the reusability probabilities of the elements (sensitivity analysis) for D16, C23, C22, and D15 (the top-four variables in the RF model).

Table 5
Rank correlation coefficients between features in the dataset (Spearman's).

	C22	C23	D11	D12	D13	D14	D15	D16	D17	D20
C22	–	0.55**	−0.08	−0.06	−0.04	−0.09	0.01	0.00	0.04	−0.15
C23		–	−0.16	−0.19	−0.10	−0.20*	−0.12	−0.18	−0.01	−0.11
D11			–	0.82**	0.65**	0.68**	0.25**	0.30**	0.50**	0.34**
D12				–	0.71**	0.71**	0.41**	0.36**	0.51**	0.35**
D13					–	0.65**	0.42**	0.54**	0.47**	0.50**
D14						–	0.42**	0.29**	0.56**	0.45**
D15							–	0.32**	0.41**	0.42**
D16								–	0.29**	0.42**
D17									–	0.34**
D20										–

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

result of the predictive models shows that the non-linear classifiers outperform the linear methods, an indication that the actual relationship between the predictors and the outcome would be non-linear.

According to Fig. 3, the most important social factor affecting reuse is the perception of the regulatory authorities about a recovered structural component. This factor was observed by Chileshe et al. [48] in the context of the South Australian building sector. According to this study, to improve the perception of the building regulators, it is essential to increase awareness of the stakeholders about the advantages of reuse [48]. Fig. 4 reveals that whenever this perception is in favour of reuse, the reusability of the structural components increases.

The second and third ranks among the social reusability factors belong to risks. These factors were reported as reuse barriers by several authors in the literature [40,45,46,49,51]. Rakhshan et al. [30] observed that there is a strong correlation between perception and risk. They argued that the potential risks associated with reusing structural elements affect the perception of the stakeholders about this intervention.

The fourth most important social factor is the perception of the stockist about the element (D15). This factor has been reported by Dunant et al. [42]. According to Dunant et al. [42], the stockists are sensitive to the visual appearance of the recovered structural elements, which could affect their perception of the reusability of these components. Based on Fig. 4, the positive perception of the stakeholders towards recovered load-bearing structural elements of a building could potentially improve their reusability.

While Table 5 portrays the one-to-one dependency of the features, based on the correlation and assuming that there are linear relationships between the variables, it does not show the complex nature of the interdependency between the variables. In this situation, it is recommended to employ Bayesian Networks (BN) to develop an easy-to-understand and interpret visual tool (based on the Directed Acyclic Graphs or simply DAG). The BN illustrates the interdependencies between the variables (both dependent and independent) using the DAG, which is learned from the data and quantifies them using the Conditional Probability Tables (CPT) for each variable (node) give the values of its parent nodes as illustrated in the learned DAG.

The BN would enable us to assess the effects of social factors (independent variables) on the social reusability of the structural elements (dependent variable) in a very efficient and straightforward way. This can be implemented using the probabilistic knowledge of predictors and their interdependencies. Initially, the authors converted the five-scale predictors to three scale variables with minus one (−1) indicating negative impact, zero (0) no impact, and one (1) positive impact. This is done for the ease of visualisation of the DAG. To distinguish the altered independent variables from the original ones, letter "C" is introduced at the end of these variables. It should be noted that the developed DAG and CPT are solely intended to depict the interdependency of the affecting variables. Hence, the results will not be further explored to develop a set of easy-to-understand rules to predict the social reusability of the elements. This task will be discussed in Section 3.3.2.

Fig. 5 shows the BN structure (or DAG) learned from the complete dataset, which is done automatically after evaluating several score-based or constraints-based methods to choose the best model [92,93].

The BN structure in Fig. 5 is learned using the Tabu search algorithm, which is one of the widely used score-based structure learning algorithms and was implemented in the R package using the "tabu" function of the "bnlearn" library. This network was selected after using different learning algorithms in the "bnlearn" package, including hill climbing (hc), another score-based structure learning algorithm, and performing cross-validation with 5-folds using the "bn.cv" function in the "bnlearn" package to compare their performances. The "hc" and "tabu" algorithms show nearly similar BN structures. However, the BIC of the network learned using the "tabu" algorithm was smaller and showed a slightly better performance.

Fig. 5 appropriately shows the interdependency of the variables and agrees with the relative feature importance levels of Fig. 3, but it is evident that the interaction between variables is not accurate. For instance, the response (E3C) affects C23C and D15C. However, the social reusability (E3C) is a dependent variable, and other variables (independent) have direct and indirect impact on it. As advised by Refs. [93,94], it is essential to discuss the resulting BN model illustrated in Fig. 5 with the domain experts and consequently revise this BN by considering experts' opinions. After consulting the auto-generated DAG in Fig. 5, learned from the data only, with several experts in this field, the BN model was revised based on the combination of data and expert opinions, as illustrated in Fig. 6. The resulting BN was also validated using several model diagnostic algorithms, as discussed above.

In the BN model proposed for modelling E3C, the strength of the link, along with the associated uncertainty, is captured using probabilities and statistical distributions, which are derived based on the observed data. Fig. 7 illustrates the learned BN with the calculated probabilities shown on each node.

From these graphs, one can see the complex nature of the interdependencies between the variables cannot be represented using the common linear modelling methods, and a more sophisticated machine learning-based approach, such as the Bayesian network, is necessary to be developed and applied for better understanding of the interactions of affecting variables on the social reusability/sustainability.

In the BN shown in Fig. 6, three nodes (D11C, D22C, and C23C) are considered as root nodes, and their parameters are learned by estimating these probabilities using the Bayes method, which estimates the parameters of the learned BN in a Bayesian way using the expected value of their posterior distribution. The estimated marginal and conditional probabilities for the variables can be updated in the light of new evidence or data using a statistical algorithm known as the Bayes rule [92,93]. Since the variables of the survey developed in this study are all categorical, the plausible prior distributions on marginal and conditional probabilities are either Beta or Dirichlet distributions, and the resulting posterior distributions will be also Beta or Dirichlet distributions with the updated hyperparameters. The details of this prior to posterior updating can be found in Refs. [92,95], and here the focus is to use the learned BN to make some inferences about the hypotheses addressed above. In particular, the learned BN can be used to compute the conditional

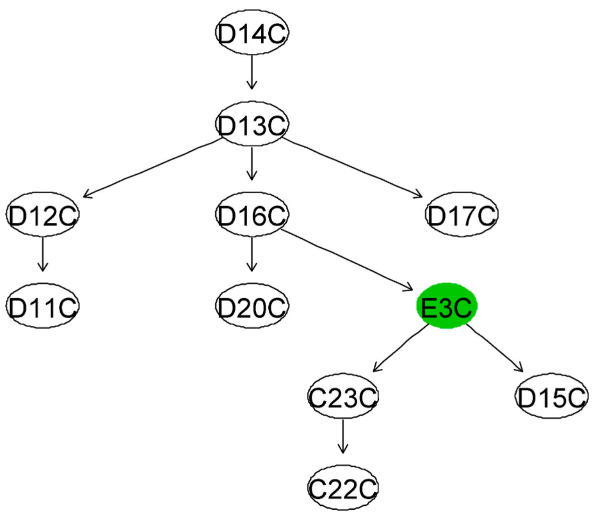

Fig. 5. The BN networked learned from the entire dataset.

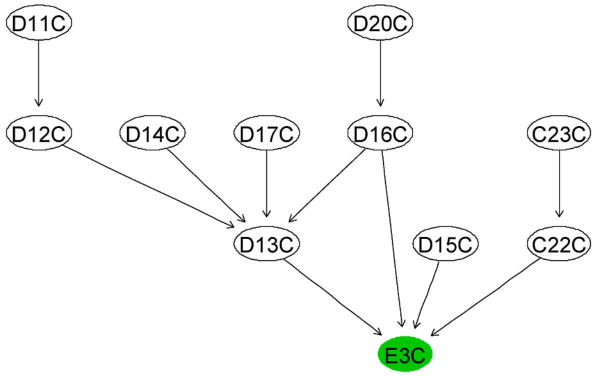

Fig. 6. The BN learned by eliciting the experts.

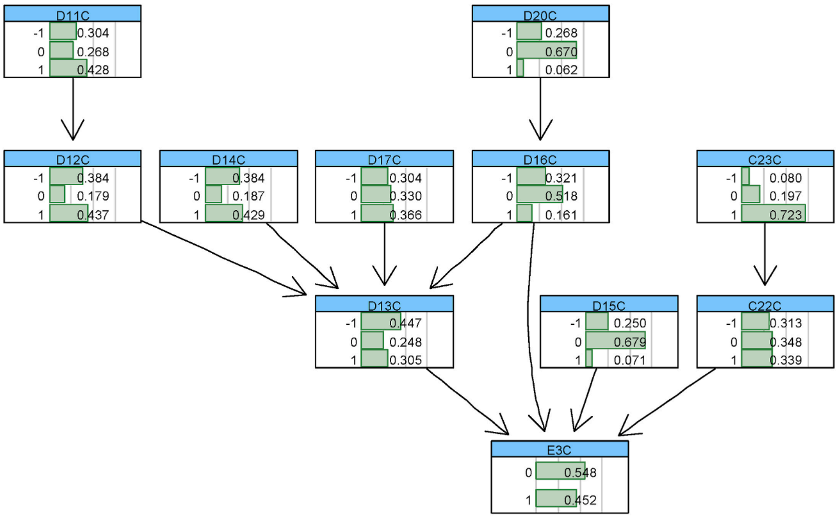

Fig. 7. The conditional probability table (CPT) of the DAG in Fig. 6.

probability of E3C given the different combination of the parent nodes, including D13C, D15C, C22C, and other variables via the parent nodes.

3.3.2. Developing an easy-to-understand learner

While the SA and visualisation techniques used in Section 3.3.1 were helpful in opening the selected RF model, they still do not provide any clear indication of how the interactions between the features can be harnessed to estimate the social reusability of the structural elements. Therefore, in this section, the authors developed a set of easy-to-interpret rules based on the selected RF model to fill this gap.

In this study, the authors followed the approach suggested by Deng [91] to extract rules from the selected RF model. First, the authors followed the validation set approach and randomly selected 70% of the observations in the dataset to train an RF model with similar hyperparameters available in Table 4. Then, using the "inTrees" package, we extracted the rules from the RF model and ranked them according to their quality (Fig. 8) [91].

In the next stage, and after a thorough investigation, only the relevant rules were retained, and the remaining irrelevant or redundant rules were removed. The resulting sets of rules were investigated to create a set of rules with the highest accuracy on the training data. These rules are reported in Table 6. It should be noted that the set of rules in Table 6 is easy to understand and interpret and considers the interactions between the variables for making predictions.

The first column in Table 6 contains the rule number, which should be followed strictly. It means that the rules should be checked sequentially, and as soon as a set of conditions satisfies the collected data on an element, the process stops. The second column is the length of the rule, which is equal to the number of conditions in column five. The third column is the proportion of the observations in the training set that satisfy the rule conditions in column five. The fourth column shows the resulting misclassification ratio made by a rule condition(s). Column five lists the conditions of a rule, and the last column shows the prediction.

Table 6 is developed based on the training dataset defined in this section. While the above set of rules provides an easy-to-understand and implement collections of conditions, it is essential to make sure that the resulting predictions on the unseen data sat-

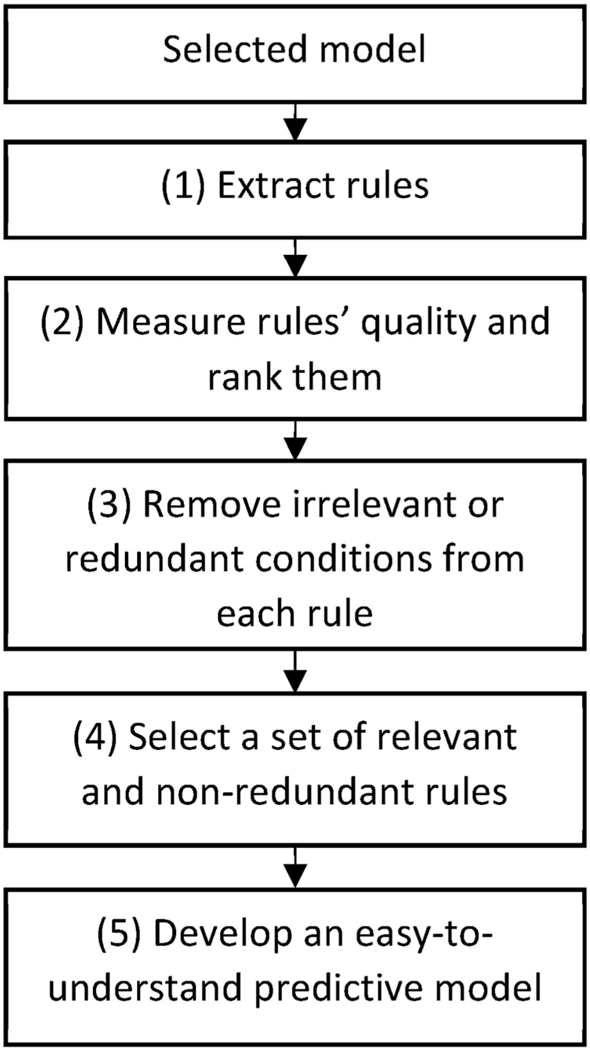

Fig. 8. The process of developing the rules set from the selected RF classifier [29,91].

Table 6
The learner (rules set) developed based on the selected RF model.

Rule No.	Length	Frequency	Error	Rule	Prediction
1	3	0.244	0	C23 > 3 & D13 = 2 & D17≤4	0
2	3	0.179	0	C22 > 3 & D11 > 2 & D12 > 1	1
3	5	0.218	0	C22≤3 & D15≤3 & D16≤3 & D17≤4 & D20>2	0
4	2	0.064	0	C23≤3 & D16≤2	1
5	2	0.064	0	D14≤2 & D17 = 3	0
6	2	0.051	0	C23≤4 & D12 = 3	1
7	1	0.179	0	Else	1

isfy the minimum requirements set in Section 3.2.4. Therefore, the corresponding testing dataset (unseen observations by the learner) was used to evaluate the performance of the learner presented in Table 6.

The learner in Table 6 made no mistakes in classifying the non-reusable components in the test set, resulting in the Type-I error rate equal to zero (0). However, it made three (3) Type-II errors by classifying reusable components as non-reusable, resulting in an overall accuracy of 91%. Therefore, this learner satisfies the minimum performance requirements defined in sections 3.2.4. Moreover, the learner in Table 6 is transparent and easy-to-understand and can be easily implemented in practice.

Appendix C summarises the survey that the practitioners need to perform before being able to use the learner in Table 6. In Appnedix C, the variable codes (Code) are kept equal to the original survey (Appendix A) to maintain uniformity.

4. Conclusion

This research, which aims to develop a probabilistic predictive model to estimate the social sustainability due to the reusability of the structural elements of a building at its end-of-life to promote the reuse rates in the building sector, is novel in several ways. By thinking out of the box, this study develops a novel methodology using various advanced ML techniques to address challenging issues the AEC industry faces, such as reusing structural elements. It is the first study that uses advanced supervised machine learning techniques (including random forest, K-Nearest Neighbours algorithm, Gaussian process, support vector machine, etc.) to develop a model that predicts the reusability of the structural elements from a social perspective. This study reveals that the relationships between variables are not linear, and thus the conventional classic statistical models are not appropriate to use. This study goes beyond all other research in this field and, for the first time, employs Bayesian Networks and experts' elicitation to visually portray the complex nature of the interdependencies between the variables. Furthermore, it is the first study that uses sensitivity analysis and visualisation techniques to open the selected black-box best-practice random forest model and rank the affecting variables. Likewise, for the first time, this research develops a set of predictive rules that can be used by professionals in the building sector for estimating the acceptance level of the stakeholders about using the recovered load-bearing structural elements in new buildings.

The easy-to-understand predictive tool developed during this research has several advantages. First, it can be used by any professional in the construction sector, who does not need to have a background in data science. Second, it gives a first-hand idea about the level of acceptance of different stakeholders regarding the reuse of structural components (i.e., social reusability). Third, it can potentially increase reuse rates, which, in turn, can assist the growth of reuse markets.

According to this paper, the perception of the regulatory authorities has the highest impact on the reusability of the structural components. The second most important factor is the potential health and safety risks. The third affecting factor is the potential liability risks for reusing the structural elements, and the fourth most important factor is the perception of the stockiest about these components.

This study concludes that none of the reusability factors in isolation can determine if an element is reusable and that the interaction between variables needs to be considered before making any decisions. The poor performance of the simple models such as the logistic regression and the outcome of the developed Bayesian network reveal that there are complex interactions between variables, which requires advanced methods to uncover such relationships and assist experts in their decision-making process. This study concludes that the complicated interdependencies among reusability factors hinder the widespread adoption of reuse since they increase uncertainty about the feasibility of reusing load-bearing structural components among stakeholders. Notwithstanding, this paper concludes that using the probability theory foundations and combining them with advanced ML techniques can provide a unique solution to complex and challenging issues facing the AEC industry, such as developing tools that can reliably estimate the social reusability of the structural elements given the affecting factors.

On the other hand, the limitations of this paper should be considered before using its results. The first limitation is the low reuse rates in the building sector, which made the task of collecting data from a larger sample size challenging. Nevertheless, probabilistic supervised machine learning methods used in this study are robust and scale well to the big and small datasets. Moreover, this study limits itself to the social reusability of the superstructure of a building. So, extending the results to the other components should be considered with care. However, the authors believe that the approach suggested in this study (Fig. 1) can be adapted to perform similar studies in other subdivisions of the construction industry.

One potential future research is to use the results of this study to estimate the social reusability of recovered load-bearing building components in case studies of relevant buildings and to evaluate the effects of this research on promoting reuse in the building sector. Furthermore, as discussed earlier, this research is limited to building superstructures. Therefore, it is recommended to carry out such investigations in other subcategories of the building and construction industry such as foundations, roads, bridges, and infrastructures.

This paper was focused on developing a model that can predict the reuse potential of structural elements at the end of the building's life and did not evaluate the causal relationship between the variables. Hence, as future research, methods such as Agent-Based Modelling (e.g. Refs. [96–98]) can be used to analyse the relationship between reusability factors. The results of such a study can be used to develop a set of guidelines to promote the circularity of load-bearing building components.

CRediT authorship contribution statement

Kambiz Rakhshan: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualisation, Writing - original draft.
Alireza Daneshkhah: Conceptualization, Writing - review & editing, Supervision.
Jean-Claude Morel: Conceptualization, Writing - review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendices. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jobe.2023.106351.

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