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Revamping Sustainability Efforts Post-Disaster by Adopting Circular Economy Resilience Practices

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Abstract: Post-disaster reconnaissance is vital for assessing the impact of a natural disaster on the built environment and informing improvements in design, construction, risk mitigation, and our understanding of extreme events. The data obtained from reconnaissance can also be utilized to improve disaster recovery planning by maximizing resource efficiency, minimizing waste, and promoting resilience in future disasters. This paper aims to investigate existing reconnaissance reports and datasets to identify the factors that impact the reusability of buildings post-disaster and to recommend strategies that align with circular economy goals. The study adopted a three-step research methodology to attain the proposed goals: (1) thematic analysis was used to evaluate types of damages reported in the reconnaissance reports; (2) a supervised machine-learning algorithm was employed to analyze reconnaissance datasets; and (3) a concept map was developed based on interviews of 109 stakeholders in disaster-prone communities to recommend strategies to adopt circular economy practices post-disaster. The study results highlight the recurring risks of damage to different parts of the building and how circular economy resilience practices like deconstruction can minimize waste and maximize resource efficiency during post-disaster recovery. The findings of the study promote a more regenerative economy to build resilience to the challenges of future extreme weather events.

Keywords: circular economy; post-disaster resilience; deconstruction; reconnaissance; disaster waste; sustainability; hurricane; health and wellbeing

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1. Introduction

According to United Nations Office for Disaster Risk Reduction, between 1980 and 2019, approximately 11,500 natural disasters were reported worldwide, and the frequency of occurrence of natural disasters has increased significantly in the last 20 years [1]. This exponential rise in the frequency of natural disasters reflects adverse consequences in public health and infrastructure damages [2]. Natural disasters also produce an enormous amount of construction and demolition waste and have had devastating consequences in both developed and developing countries. Common challenges faced by both developed and developing countries post-disaster include the management of disaster waste, lack of resources for reconstruction, and lack of affordable housing [3,4]. Klotzbach et al. (2018) highlighted that the increase in damages to buildings and infrastructure during hurricanes from 1900 to 2017 is largely due to societal factors such as an increase in population and settlement along the U.S. Gulf and East Coasts [5]. The study highlighted the fact that coastal communities need to adopt sustainable and resilient practices to adapt to the increasing frequency of hurricanes in these regions. However, disaster-prone communities like coastal cities in the U.S. tend to make an effort towards the recovery of pre-event conditions rather than integrating innovative, resilient, and sustainable practices during the recovery phase to increase the adaptive capacity of communities [6].

One of the critical post-disaster activities for faster recovery is an early reconnaissance of hurricane damage. Different organizations have been established for post-disaster reconnaissance of hurricane damage in the Caribbean and North America. Structural Extreme Events Reconnaissance (StEER) is one such organization formed by a consortium of universities to develop resilience in disaster-prone communities by producing new knowledge on the built-environment performance through impactful reconnaissance of damaged buildings after natural disasters [7]. Post-disaster reconnaissance includes a comprehensive assessment of the damage to the built environment such as that to buildings, infrastructure, and other physical structures in the affected areas following a natural disaster, like a hurricane, to accelerate recovery efforts [8]. The assessment process involves various techniques such as visual inspection, surveys, and other types of data collection, which are typically conducted by trained professionals including forensic engineers and emergency management officials. Klepac and Cleary (2022) highlighted that reconnaissance data provide significant information about the performance of buildings and factors that impact the performance during a hurricane [9]. The study indicated that factors such as roof shape and roof covering significantly affect the performance of the building. Additionally, with the introduction of the Florida Building Code (FBC) in 2002, there was a reduction in extensive damage to homes in hurricane impact areas, with significantly less damage to newer homes. Similarly, Hatzikyriakou et al. (2016) highlighted that building distance from large water bodies/coasts, building age, and building elevation off the ground are the major factors that impact the vulnerability of a building to damage from a hurricane and its performance [10]. On the other hand, Yeum et al. (2019) developed a unique approach for the rapid and autonomous classification of post-disaster reconnaissance building images that will facilitate engineers and researchers to readily and easily find reports of special interest [11]. Such an autonomous organization of data would significantly improve understanding of the scale of impact and any trends in damages.

Kijewski-Correa et al. (2022) conducted a field study in the Bahamas when a category 5 storm, Hurricane Dorian, made landfall in September 2019 with a sustained wind speed of 295 km/h [12]. The study highlighted that storm surge caused significant damage to the interior finishes and partitioning of buildings, which did not have any structural damage based on forensic assessment. Since many of these buildings did not have any insurance coverage, there was a significant delay in the recovery process, and the reusability of the buildings was impacted. A natural disaster such as a hurricane creates a multi-hazard environment in which buildings are vulnerable to both wind and flood damage [13]. Many insurance agencies do not typically reimburse repair costs if the homeowner does not have flood insurance, and it is unclear whether damages are caused by flood or wind [14]. Consequently, hurricane-prone communities face severe financial strain, which delays the recovery and reusability of buildings. Similarly, Lamba-Nieves and Santiago-Bartolomei (2022) highlighted that low-income households in Puerto Rico are on the verge of being displaced after the impact of Hurricane Maria due to their inability to access aid from the Federal Emergency Management Agency (FEMA)'s Individual Assistance (IA) program [15]. The study highlighted that many vulnerable communities across the U.S. have faced similar challenges due to denial of support or aid caused by administrative and procedural criteria that low-income communities are unable to meet. Experiencing a natural disaster and undergoing reconstruction is a stressful and anxiety-provoking experience for many low-income communities [16]. As such, there is a pressing need to adopt resilient practices to improve the health and wellbeing of people during post-disaster recovery.

Recurring natural disasters like hurricanes can cause social disruption, as communities are disrupted, and individuals are displaced [17]. Such social disruption leads to the breakdown of social networks and support systems. As such, individuals and communities also become powerless to prevent and mitigate the impact of disasters [18,19]. One of the effective solutions to reduce the financial strain on homeowners is adopting the building deconstruction method during post-disaster recovery. Deconstruction is a method for faster recovery of building products, parts, materials, and components to minimize environmental impact and maximize economic value through reuse, recycling, repair, and remanufacture [20]. Denhart (2009a) highlighted that the adoption of the building deconstruction method instead of demolition in the aftermath of Hurricane Katrina empowered the victims of the hurricane in terms of: (1) relief achieved through the philanthropic contribution of minority contractors; (2) recovery of salvage materials for reuse or recycling and donation of salvage materials; (3) regain of control of their property and retained wealth; and (4) change in attitude towards green practices [21,22]. The study highlighted that the deconstruction program initiated by Mercy Corps had a transformative impact on the disaster-prone community in terms of cultural, emotional, and psychological implications. Hence, similar efforts and investments need to be made in the future after natural disaster impacts, such that they empower victims of natural disasters and improve the mental health and wellbeing of impacted communities.

However, to this end, the reconnaissance efforts do not focus on the deconstruction and recycling or reuse potential of building components in the aftermath of a natural disaster. Therefore, this study aims to: (1) investigate different types of damages observed during the early reconnaissance of six major hurricane impacts using thematic analysis; (2) analyze the damages observed in thousands of buildings during Hurricane Irma's impact, such that the factors impacting building reusability can be investigated through a machine-learning algorithm; and (3) conduct 109 interviews with different stakeholders to identify ways to reduce the disposal of disaster debris such as those generated during natural disasters and demolition, among others, in the landfill through a concept-mapping technique. The research is guided by three research questions: (1) What are the different types of damages observed in buildings during major hurricane impacts? (2) What are the critical factors that influence the reusability of buildings post-hurricane impact? (3) How can we reduce disaster debris disposal in the landfill post-hurricane impact?

2. Materials and Methods

This study utilized Design Safe cyberinfrastructure [23], an open-source database, to investigate damages observed in the aftermath of different hurricanes and identify factors that impact the reusability of the building after hurricane impact. The study is structured into three phases, where each phase is connected to the previous phase, as shown in Figure 1. First, the study conducted a thematic analysis of available Structural Extreme Events Reconnaissance (StEER) reconnaissance reports using NVIVO data analysis software (NVivo version 12) to code different themes that exist in the literature and map different trends related to types of damages observed in different hurricanes [24]. StEER is a network that works with extreme event reconnaissance organizations and the Natural Hazards Engineering Research Infrastructure (NHERI) to: (1) understand the extent of the impact of extreme events like a hurricane on the community; (2) coordinate with a network of members for early reconnaissance of disaster-affected areas to make impactful responses to disasters and accelerate the recovery process; and (3) improve community-driven standards, best practices, and policy and accelerate learning from natural disasters [23]. Secondly, the study focused on damages observed in 1122 buildings after the impact of Hurricane Irma in Florida available in the Design Safe database [25]. The authors selected the Hurricane Irma dataset because it is the only large, relevant dataset available in the Design Safe database that incorporates details about building reusability based on observed damages. The obtained large dataset is then analyzed using a machine-learning algorithm to identify different factors that impact the building's reusability in the aftermath of hurricane impact. Lastly, the study also conducted 109 interviews with homeowners, forensic engineers, contractors, project managers, and consulting engineers, among others, to identify solutions to increase the reusability potential of buildings and salvage materials in disaster-prone zones. The obtained data were then analyzed using the concept-mapping technique. The succeeding sections discuss the procedures used for thematic analysis, machine-learning analysis, and concept mapping.

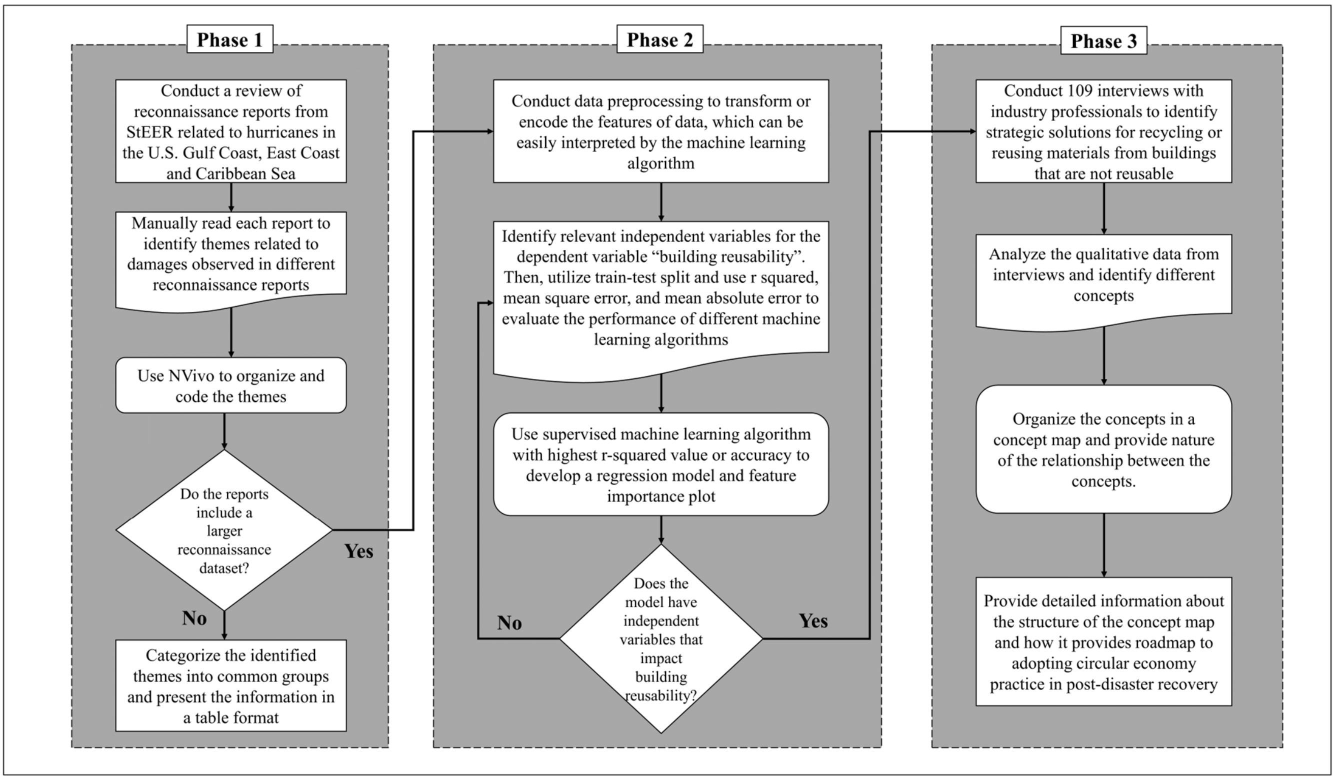

Figure 1. Research framework showing the connection between each phase.

2.1. Thematic Analysis

Thematic analysis is a method to identify, analyze, and interpret patterns of meaning within qualitative data [26]. The primary goal of thematic analysis is to construct themes to reinterpret, connect, or reframe elements of the data. The themes developed in this method are actively constructed patterns obtained from a dataset to address a research question through coding [27], as shown in Figure 2. In the first stage, the literature obtained from the Design Safe database was coded using the elemental and exploratory coding approach. The elemental coding method is the first step of thematic analysis, in which a focused review of data is used for developing foundations for future coding, and the exploratory method focuses on experimental and empirical coding of the data [28].

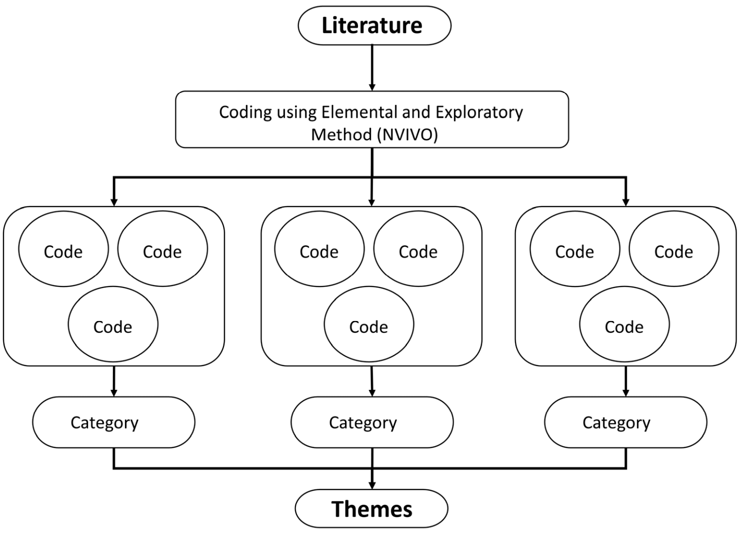

Figure 2. Step-by-step process of thematic analysis in NVIVO.

The authors developed relevant categories and sub-categories for each topic from the existing literature after coding information. Only six StEER reconnaissance reports from recent hurricane impacts were available in the database. Therefore, the authors downloaded these reports from the Design Safe database to investigate different building damages observed post-disaster. These damages were categorized into different categories such as destroyed, major damage, minor damage, and inaccessible location based on Federal Emergency Management Administration (FEMA) guidelines [29]. Each of these categories had a sub-category including roof, interior, foundation, or whole building structure to determine which parts of the building had prominent damages. Therefore, the analysis provides a comprehensive understanding of different building parts that are commonly damaged and cannot be reused or recycled.

2.2. Machine-Learning Algorithm

To identify the most effective regression model that is capable of predicting the reusability of buildings after hurricane impact with high accuracy, the authors made a comparison between the most widely used supervised machine-learning algorithms [30]. The authors then utilized a train-test split to evaluate the performance of different algorithms. The dataset was split into a training and test set in an 80:20 ratio, such that it can fit different models on the training set, and the performance of the test set can be evaluated using r squared, mean square error, and mean absolute error. The algorithms tested in this study are discussed below.

A. Decision tree: A decision tree is an algorithm for regression and classification problems that are generally utilized to develop a tree-based model [31]. Each node in the decision tree represents an attribute, and each branch highlights the outcome of the attribute test. On the other hand, each leaf provides details about the decision taken after the computation of all the attributes.
B. Random forest regressor: A random forest regressor is an ensemble learning method that combines multiple decision trees to make more accurate predictions of a continuous numerical value (i.e., a regression problem) based on a set of input features [32,33]. It is a popular technique that can handle both categorical and numerical data and easily identify important features for prediction.
C. Linear regression: Linear regression is a supervised machine-learning algorithm that is used to predict continuous numerical values based on a set of input features, such that it can find linear relationships between the input features and the output variable [34]. Linear regression is a simple and interpretable algorithm, making it easy to understand.
D. K-nearest neighbor (KNN): KNN is a machine-learning algorithm used for classification and regression to find the k-closest data points in the training data to a new data point and make predictions based on the majority class or average value of the k-nearest neighbor [35].
E. Gradient boosting: Gradient boosting is an ensemble learning method that combines weak models to create a strong model by iteratively adding weak models to the ensemble, with each new model correcting the errors of the previous ones [36]. It is a powerful algorithm that can handle complex non-linear relationships in the data.

The study defined building reusability as the dependent variable for developing a regression model using a supervised machine-learning algorithm. On the other hand, the independent variables included building age, roof cover damage, roof structure damage, wall structure damage, wall cover damage, number of stories, wall sheathing, window damage, and door damage. Since these were the only variables available in the dataset, other independent variables that could impact building reusability have not been considered in the analysis. To ensure the quality of the results from the regression analysis, the dependent variable must be continuous and should be approximately normally distributed. Therefore, a normality test was initially performed, where most of the data satisfied the conditions of normalization of data to proceed with the analysis. Additionally, the independent variables in the regression models were tested for multicollinearity. Multicollinearity is an interdependency condition that shows the symptom of poor experimental design. If the independent variables for the regression model are multicollinear, then this indicates that there are large variances in regression coefficients as well as the low information content of observed data and the low quality of the resulting parameter estimate. Therefore, the independent variables in the model were found to have a lower Pearson's correlation coefficient, indicating that there is no multicollinearity issue in the regression model.

After identifying the machine-learning algorithm with the highest accuracy, the authors developed the regression model and evaluated the impact of each variable using a feature importance plot. The feature importance plot shows the relative importance of each feature in the model. It can help identify which features are most predictive of the target variable [37]. The study utilized R-squared to check the accuracy of the machine-learning algorithm. This is a common metric that measures the proportion of the variance in the target variable that can be explained by the model. The study also calculated the mean square error (MSE) and mean absolute error (MAE) to determine the reliability of the model. The mean square error is a measure of the quality of an estimator, indicating how close the estimator is to the true value of the quantity being estimated. In the context of a regression model, MSE measures the average squared difference between the predicted values and the actual values. Lower MSE and higher R-squared values indicate better performance of the model. On the other hand, the mean absolute error measures the average magnitude of the errors in a set of predictions, without considering their direction. A value of 0 for MAE would mean that the model's predictions are perfect, and a value of 1 would mean that the predictions are off by an average of 1 unit.

2.3. Semi-Structured Interview

An Institutional Review Board (IRB) approval was pursued to maintain the confidentiality of any personal or proprietary information collected during semi-structured interviews from individuals that provided data to support the research effort. Semi-structured interviews are an exploratory method that relies on asking open-ended questions within a predetermined thematic framework [38]. This study adopted a semi-structured interview approach, because it allows for the collection of comparable and reliable data and the flexibility to ask follow-up questions and design a conceptual framework [39]. The authors conducted semi-structured interviews through the purposive sampling method, which is a judgmental sampling technique in which the individuals are selected to be part of the sample based on the researcher's judgment as to which individuals would be most useful or representative of the entire population. Similarly, the snowball sampling technique was implemented to increase the reach of the project by requesting the targeted individuals to suggest other individuals with similar expertise [40]. The authors targeted different stakeholders who are involved in the post-disaster recovery phase to document their experience and understand the challenges of adopting deconstruction from the perspective of different professionals who play a unique role in the ecosystem. As shown in Figure 3, the authors conducted 109 interviews with stakeholders, including 18 homeowners, 29 consulting engineers, 24 contractors, 12 forensic engineers, 4 lawyers, 4 LEED professionals, 8 project managers, 3 city code inspectors, 4 building materials and tools suppliers, and 4 insurance staff who had hands-on experience with post-disaster recovery challenges, especially during extreme weather events. The interview questions mainly focused on the experience of each stakeholder during the post-disaster recovery phase, challenges related to adoption of building deconstruction, aspirations related to circular economy practices, and recommendations about effective post-disaster recovery.

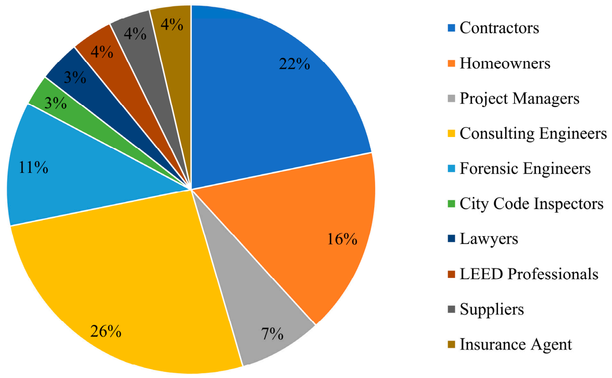

Figure 3. Distribution of stakeholders participating in the interview, n = 109.

According to Noble and Smith (2015), qualitative studies such as semi-structured interviews rely on the concepts of truth value (i.e., clear and accurate presentation of participants' perspectives), consistency (i.e., the trustworthiness of the adopted methodology), and applicability (consideration for replicability of methods and findings in a different context, setting, or group) to ensure the credibility of the study findings and to show that the study has considered a representative sample [41]. To satisfy the truth value, this study conducted 109 interviews using the purposive and snowball sampling method to reach a point of saturation. Saturation is the point at which collecting new qualitative data yields redundant information or has no significant addition to what has been collected and analyzed [42]. The authors used coding in NVIVO version 12 to conduct thematic analysis, organize themes, and test the attainment of saturation. Secondly, this study achieved consistency through the triangulation of data. To achieve this, the authors utilized different sources or different kinds of data such as the literature and Federal Emergency Management Administration (FEMA) and Environmental Protection Agency (EPA) reports to check whether they provide a consistent meaning or interpretation. This method not only established trustworthiness but also validated the concept map created from the thematic analysis. Thus, the methodology used in this study is easy to adopt and can be replicated in different contexts, settings, or groups to achieve applicable results with practical application.

The obtained qualitative data from the interviews were analyzed and represented through a concept map. A concept map is a commonly used method to analyze themes, interconnections, and findings in qualitative research [43]. One of the advantages of a concept map is that it supports the theoretical underpinning of qualitative data and helps to lay out linkages, reduce the data volume, and provide a complete picture of the solution being presented for the given problem. Conceição et al. (2017) highlighted the strengths, limitations, and scope of three different approaches for using concept mapping as a tool, which include relational, cluster, and word frequency [44]. The study demonstrated some ways to determine the applicability of different concept map approaches, which include: (1) the use of word frequency for analyzing a significant amount of textual data; (2) the use of a cluster approach to analyze qualitative data using a quantitative approach; and (3) the use of a relational approach to concept mapping for showing the relationship between concepts that are connected by a line that links two concepts. This study utilizes a relational concept-mapping technique: (1) to organize and represent knowledge on selective dismantling and recycling or reuse of salvage materials post-disaster; and (2) to understand the theory, concepts, and the relationship between them. This study used Cmap tools to construct the concept map based on the obtained themes. The Cmap tool is the most commonly used tool for constructing and modifying concept maps developed at the Institute for Human and Machine Cognition [45].

3. Results

This section presents the results of the thematic analysis of Structural Extreme Events Reconnaissance (StEER) reports, machine-learning analysis of Hurricane Irma reconnaissance data, and a circular economy resilience framework to reduce disaster debris in landfills and promote resource efficiency based on semi-structured interviews. The results are divided into three phases. The first phase highlights different types of damages observed during the early reconnaissance of six major hurricane impacts that were the only reports available in the Design Safe database. The results of the first phase provide a broader perspective on common damage patterns observed in buildings after hurricane impact. The second phase narrows the focus to damages observed in thousands of buildings during Hurricane Irma's impact, such that the factors impacting building reusability can be investigated through a machine-learning algorithm. On the other hand, the third phase provides recommendations on ways to reduce disaster debris disposal in the landfill through concept-mapping techniques based on the qualitative data obtained from 109 interviews with stakeholders.

3.1. Thematic Analysis of Extent of Building Damage Post-Disaster

This phase investigated the first research question by conducting a thematic analysis of StEER reports that provided information on different types of building damages after a hurricane event. Table 1 shows the thematic framework developed based on coding in NVIVO. The authors identified themes in this stage by following the guidelines of the deductive coding process (i.e., a top-down process in which coding is started with a set of pre-determined codes, and excerpts are identified to fit those codes). First, the extent of damage observed in reconnaissance was coded into the first-tier node, and sub-factors were coded into the second tier. With this coding system, the level of damage to different building components was identified in the six most recent powerful hurricanes that have been assessed by the StEER team, and these were the only available reports in the Design Safe website database. The six studied hurricanes included: (1) Hurricane Irma (Category 5, 2017); (2) Hurricane Florence (Category 4, 2018); (3) Hurricane Michael (Category 5, 2018); (4) Hurricane Dorian (Category 5, 2019); (5) Hurricane Laura (Category 4, 2020); and (6) Hurricane Ida (Category 4, 2021).

Table 1. Themes for patterns of building damages in the six most recent and powerful hurricanes.

Extent of Damage	Building Component	Description	References
Destroyed	Whole structure	1. Hurricane Michael completely wiped several older homes built during the 1970s era from their foundations in Mexico Beach, Florida. 2. Hurricane Dorian completely destroyed several homes, especially small cottages with slab-on-grade foundations and structures elevated at heights from 4 ft up to approximately 8 to 10 ft on concrete columns in the Bahamas. 3. Hurricane Laura completely destroyed several mobile/manufactured homes in Louisiana. 4. The combination of high wind and storm surge from Hurricane Ida caused the complete structural collapse of several residential buildings in New Orleans. Several elevated houses were swept off their pilings.	[7,46–48]

Table 1. *Cont.*

Extent of Damage	Building Component	Description	References
Major damage	Roof	1. Hurricane Irma caused the uplift of portions of the wood roof structure in a few single-family residential homes near Ponte Vedra, FL. Large sections of the roof were also removed in a group of condominiums due to hurricane wind near Crescent Beach, FL. 2. Major damage to a pre-Florida Building Code (FBR) 2002 roof was observed in a five-story hotel building in Key West during Hurricane Irma impact. 3. Hurricane Michael caused major damage to residential buildings, with loss of sheathing and framing in the roof system in Mexico Beach, Florida. 4. Hurricane Laura caused major roof cover failures in early 2000-era houses with older asphalt shingle roofing systems. During hurricane wind, shingles were torn away, initiating roof cover failures within reattachment zones where positive pressures were produced with a field of the roof. 5. During Hurricane Ida, many single-family residences had failures of roof coverings, including asphalt shingle and discontinuous metal roofing systems, that consequently resulted in extensive water leaks.	[7,47,49,50]
	Wall system	1. Hurricane Irma caused the collapse of several upper-story walls in three of the three-story condominium buildings near Crescent Beach, FL. 2. Ten single-family homes in Marathon suffered severe damage to walls, sliders, windows, and doors during Hurricane Irma. 3. Hurricane Florence caused major damage in 21 residential buildings, including wind-driven damage to the building envelope and loss of vinyl siding and asphalt shingles, within North Carolina. 4. Some of the metal buildings in the Bahamas had major damage due to the loss of the building envelope during Hurricane Dorian. 5. Structural failures such as the collapse of gable end walls caused by the lifting of exterior walls within light-framed wood metal plate trusses were observed during Hurricane Ida's impact in New Orleans.	[7,46,49,50]

Table 1. *Cont.*

Extent of Damage	Building Component	Description	References
Major damage	Foundation	1. After Hurricane Dorian's impact in the Bahamas, several wall-to-foundation failures were observed despite the presence of anchor bolts. 2. Many elevated houses were severely damaged when the connection of the superstructure to the piles failed during Hurricane Ida's impact in New Orleans. 3. Many mobile/manufactured homes were prone to overturning from high winds caused by poor anchorage practices during Hurricane Ida in New Orleans.	[7,46]
Minor damage	Roof	1. Building structures in Miami suffered minimum damage to the barrel tile roofs during Hurricane Irma. 2. Hurricane Florence caused minor damage to roof shingles and siding of 38 residential buildings. 3. During Hurricane Laura's impact in Louisiana, modern residential construction had minimal damage, such as minor roof cover loss and garage door failures.	[48–50]
	Wall system	1. Isolated retail buildings had a failure of wall cladding systems as well as partial collapse during Hurricane Laura.	[48]
Inaccessible	Whole structure	1. Extensive flooding was observed in a few neighborhoods in Naples, due to which the buildings were inaccessible for assessment during Hurricane Irma. 2. Some of the residential houses along the eastern shore roads of the Bahamas were not accessible for assessment during Hurricane Dorian's impact. 3. During Hurricane Laura, street view surveys were conducted, but these were not able to discern interior damage due to water ingress.	[46,49,50]

3.2. Machine-Learning Analysis to Predict Building Reusability

The study utilized the Hurricane Irma dataset from the Design Safe database to investigate the second research question, because it was a larger dataset with many variables in comparison to other reconnaissance datasets available in the database. In particular, the dataset consisted of 1122 pieces of data related to damage observed in different types of residential buildings and the potential reusability of the building. This study developed a regression model by identifying the regression statistical analysis with the highest accuracy using a machine-learning technique referred to as a train-test split. Table 2 shows the accuracy, mean absolute error (MAE), and mean square error (MSE) of different machine-learning algorithms in a train-test slip test. The train-test split test of five different machine-learning algorithms indicated that decision tree, random forest, linear regression, KNN, and gradient boosting have an accuracy of 0.394, 0.654, 0.483, 0.24, and 0.667, respectively. Since the gradient-boosting algorithm has the highest accuracy, it is selected as the algorithm for the regression model for this study. An R-squared value of 0.667 indicates that 66.7% of the variability in the actual reusability of the building can be explained by the predicted reusability using the model. It also indicates that the model has moderate predictive power.

Table 2. R-squared value of different machine-learning algorithms in a train-test split test.

S.N.	Machine-Learning Algorithm	Accuracy	MAE	MSE
1.	Decision tree	0.394	0.135	0.357
2.	Random forest	0.654	0.113	0.259
3.	Linear regression	0.483	0.213	0.213
4.	K-nearest neighbor	0.240	0.384	0.384
5.	Gradient boosting	0.667	0.129	0.253

In the context of predicting building reusability using a gradient-boosting algorithm, the model obtained an MAE of 0.129, which means that on average, the model's predictions are off by 0.129 units of reusability. This could be considered a relatively low error, based on the scale and distribution of the reusability values in the dataset. Similarly, the model obtained a value of 0.253 for MSE, which indicates that on average, the predicted reusability values are 0.253 units away from the actual reusability values. Such a lower MSE value indicates better model performance, as it means the model's predictions are closer to the actual values.

The study also developed a feature importance plot for the gradient-boosting regressor model. Feature importance values are calculated based on how much each feature in the regressor model contributes to reducing the mean square error in the model. Features that are used more often in splitting the training data in the model and lead to greater reductions in the mean square error are assigned higher importance values. As shown in Figure 4, the feature importance plot shows the most important feature for predicting building reusability. The importance of each feature in the order of decreasing importance are roof structure damage (0.467), roof cover damage (0.160), wall sheathing damage (0.118), building age (0.101), wall cover damage (0.054), door damage (0.042), window damage (0.039), number of stories (0.009), and wall structure damage (0.007). These values indicate the importance of each feature and determine the degree of usefulness of a specific feature for the current model and prediction of building reusability. If a feature has a lower value, such as that of wall structure damage (0.007), then it will have a smaller effect on the model that is being used to predict a certain variable. On the other hand, a higher value, such as that of roof structure damage (0.467), means that the extent of damage to the roof structure has the highest impact on the predicted building reusability score. These results align with the findings in the literature, which indicated that roof structure is an important factor that impacts the performance of a building during a hurricane and after hurricane impact [9]. Since damage to the roof structure is very common during hurricane impact, as indicated by the results of phase 1, many buildings are recommended to be demolished when they are not reusable. This traditional approach not only causes financial strain on homeowners but also overwhelms landfill sites due to the sudden inflow of disaster debris as well as demolition waste [21]. As such, it is critical to adopt circular economy practices such as deconstruction methods and design for disassembly principles to maximize the reuse and recycling of building components post-disaster. The information from the feature importance plot can be used to prioritize repairs and maintenance efforts for buildings in order to maximize their reusability.

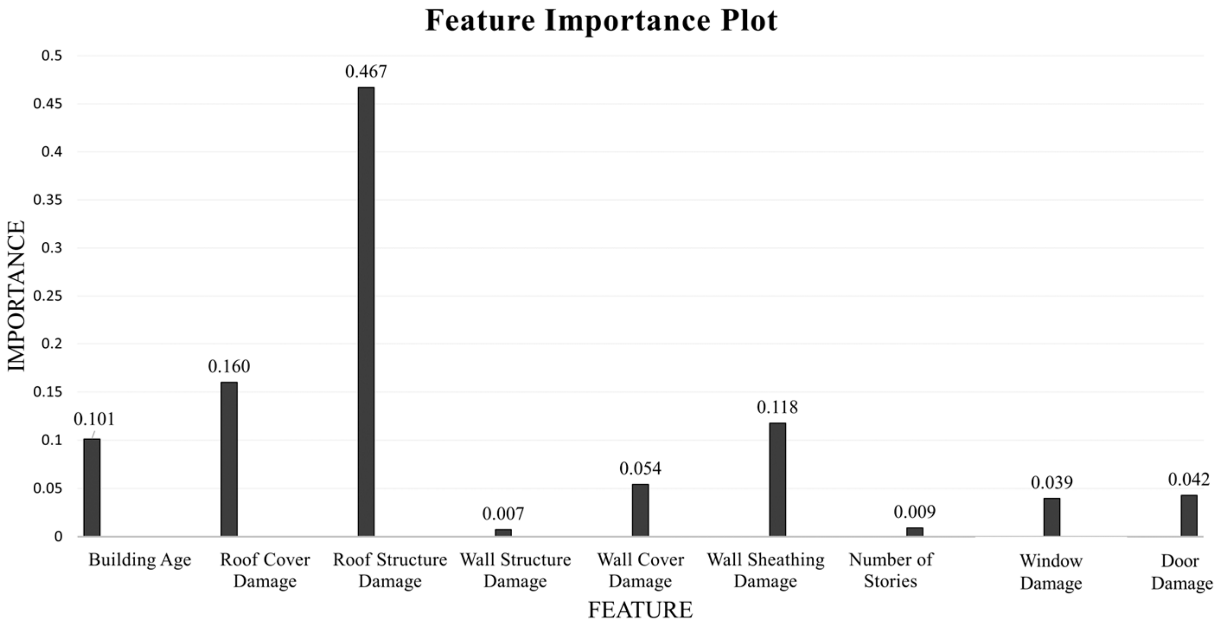

Figure 4. Feature importance plot for gradient-boosting regressor model.

3.3. A Framework for Circular Economy Resilience during Post-Disaster Recovery

The authors collected qualitative data through semi-structured interviews of 109 stakeholders in seven weeks. Out of 109 stakeholders, 91 stakeholders had industry experience. Overall, 38 professionals had 1–10 years of experience, 16 professionals had 11–20 years of experience, 12 professionals had 21–30 years of experience, 10 professionals had 31 to 40 years of experience, and 6 professionals had more than 40 years of experience. Many homeowners indicated that they have an emotional investment towards their property and developed trauma from living through a hurricane. After the hurricane impact, their mental health and wellbeing were severely impacted when they could not recover their property due to lack of access to funding and resources. They reported that if services were available that would allow them to recover salvage materials from their home, they would adopt a deconstruction approach to repurpose the materials so that they could reduce the cost of reconstruction. Similarly, consulting engineers who assessed damages after Hurricane Ian impact indicated that many houses in Naples, Florida had flooding on the first floor, which generated mold post-disaster, whereas the second floor had no damages. In such cases, homeowners are recommended to demolish the house by consulting engineers/forensic engineers, even if salvage materials can be recovered from the second floor of the house. Similarly, as reported by forensic engineers, damage to the roof is extremely critical, because the roof is important for protecting the materials inside. They indicated that if 50% of the building is damaged, it is considered a total loss by FEMA and insurance companies. Such buildings are also recommended to be demolished by forensic engineers and consulting engineers. As reported by a demolition contractor, the choice of the method during demolition would depend on what would be the cheapest for the owner and the fastest during the permitting process. However, insurance agents indicated that low-income families normally do not have insurance, and sometimes they cannot access public funds for demolition and reconstruction. Therefore, deconstruction can be a potential solution for the recovery of salvage materials, which can later be used in low-income house construction for underprivileged families who cannot afford demolition and reconstruction. Based on deconstruction contractors, deconstruction can be used for cost-efficiency and can reduce any generation of waste during the restoration process. The contractor also indicated that a significant amount of salvage materials can be diverted from the landfill to help underprivileged families. Moreover, the contractor also reported that all buildings may not be suitable for deconstruction, and only those inhabitable buildings that have non-structural damages, buildings that need to be relocated, and buildings with partial damages with a lower cost of reconstruction in comparison to repair can be assessed properly for safe deconstruction.

Figure 5 shows a conceptual framework developed by conducting a thematic analysis of the interview data in NVIVO. The concept map is developed using the relational concept-mapping technique to address the third research question. The concept map is built upon the feedback obtained from 109 industry professionals to provide a framework that maximizes the adoption of circular economy practices. This framework provides organized knowledge on the selective dismantling and recycling or reuse of salvage materials post-disaster to understand the theory, concepts, and the relationship between them. The structure of the concept map is represented in a non-linear manner, with several feedback loops that provide a complete picture of the list of things that should be considered for recapturing, recycling, and reusing disaster debris through deconstruction. The phase 2 results indicated that those buildings with significant damage to the roof structure are not considered to be reusable. Consequently, thousands of buildings are generally demolished, and the waste produced is diverted to the landfill for disposal [51]. However, natural disasters like hurricanes produce a significant amount of disaster debris, and landfill sites are overwhelmed by such waste. Additionally, there is a sudden surge in demand for construction resources among disaster-prone communities due to simultaneous projects being initiated by local, private, governmental, and international organizations.

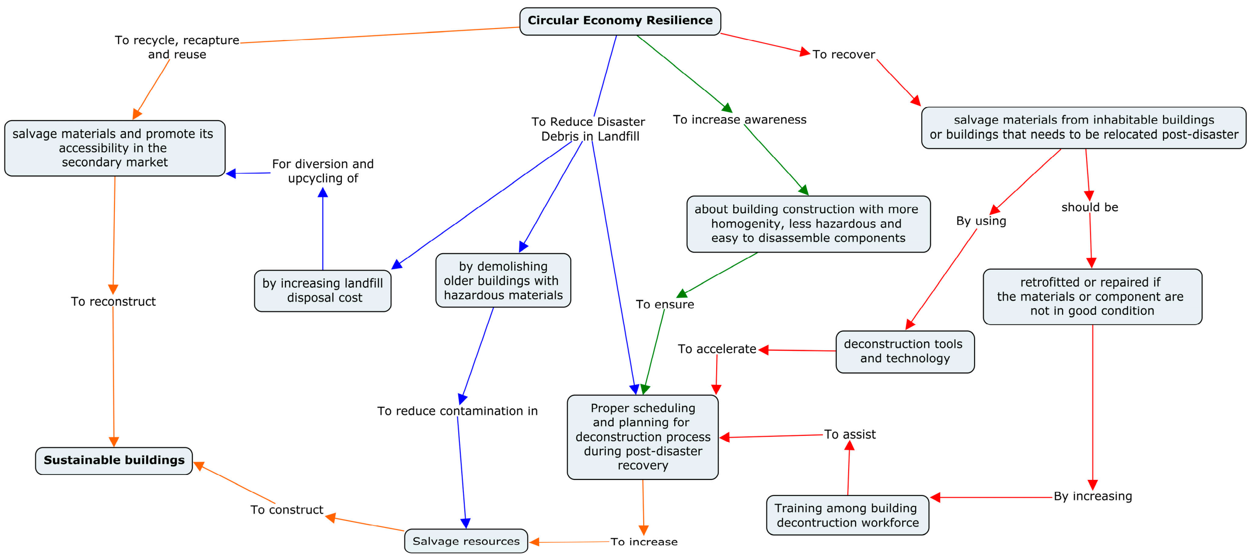

Figure 5. Concept map showing different strategies to achieve circular economy resilience post-disaster.

Therefore, the concept map framework shows different concepts related to strategies for achieving circular economy resilience post-disaster based on the feedback reported by interview participants. The concept map consists of four different ways of achieving circular economy resilience, which can be distinguished through color-coded arrow lines. First, the strategies guided by the orange line indicate that it is essential to promote the accessibility of salvage materials in the secondary market and to develop a proper schedule and plan for the deconstruction process. In order to achieve this objective, the strategy guided by the blue line highlights that it is important to encourage stakeholders to reduce disaster debris disposal in landfills by: (1) demolishing older buildings with hazardous materials, such that this would reduce contamination of salvage materials; (2) recovering salvage materials by proper scheduling and planning for the deconstruction process; and (3) increasing landfill disposal cost to encourage diversion and upcycling of salvage materials.

The strategy guided by the green line demonstrates the importance of educating stakeholders about designing and constructing buildings with more homogeneity, less hazardous materials, and materials that are easy to disassemble. For easy disassembly of a building, a design for disassembly (DfD) principle should be adopted, which includes: (1) the use of an open building system, modular design, and assembly technologies; (2) easy access to all parts of the building and all components; (3) joints and connectors designed to withstand repeated use; (4) allowing for parallel disassembly; (5) the use of prefabricated subassemblies and a system of mass production; and (6) development of a database for the building manufacture and assembly process [52,53]. As reported by a deconstruction contractor in the interview, a normal deconstruction project involving 8 to 10 workers in a 2000 sq. ft. house will take 3 days to complete and will result in 40% cost savings in comparison to demolition. Therefore, it can be inferred that deconstruction of inhabitable buildings are a feasible and viable solution for reducing waste disposal in landfills. The adoption of a DfD principle would help to deconstruct or maintain buildings after future extreme weather events.

Lastly, to recover salvage materials from inhabitable buildings or buildings that need to be relocated post-disaster, deconstruction tools and technology should be utilized to accelerate the deconstruction process. Additionally, the condition of recovered components or materials should be properly assessed for any defects, and these should be retrofitted or repaired before utilizing them during reconstruction of new building. Hence, it is essential to train as many deconstruction workforce personnel as possible and to educate them about these strategies, such that the construction of new buildings meet the standards of the building code. Overall, the conceptual framework in Figure 5 provides all the concepts and relevant strategies within a picture for achieving circular economy resilience post-disaster and fostering sustainable post-disaster recovery in disaster-prone communities.

4. Discussion

The results of phase 1 show that during Hurricane Dorian, Hurricane Florence, Hurricane Ida, and Hurricane Irma, the StEER team observed damages to the building envelope, roofs, and exterior walls in several residential buildings. The results of machine-learning analysis indicated that the roof structure has the highest impact on the predicted building reusability. Since buildings with roof damage have no protection against external forces such as wind, rain, and heat, homeowners are less likely to be able to reside in the building due to such structural damage. As reported by contractors interviewed in the study, a damaged roof structure needs to be replaced with updated building codes and design. For instance, a pyramidal-shaped roof should be used during repair instead of a gable-ended or hip-shaped roof due to its resistance to uplift during impact of hurricane winds. They also indicated that retrofitting the damaged building up to the latest high-wind requirements is neither practical nor cost-effective unless the homeowners aim to rebuild the entire house. They reported that they generally use roofing cement if there are minor damages and holes or new metal roofs if there are major damages in the roof structure. However, according to forensic engineers interviewed in the study, building damage repairs are arduous for many homeowners due to inflation, difficulty in getting insurance claims, incompatibility of old and new materials, and expensive new construction methods. Additionally, lower-income homeowners are less likely to start reconstruction or repair due to their struggle to gain access to federal funding and recovery resources [54].

Maldonado et al. (2016) highlighted that across the country, communities of color and low-income communities who reside in hurricane-prone areas do not have the financial resources or access to credit to make their homes safer before a disaster (e.g., by raising a home on pilings to avoid floodwaters) [55]. Moreover, they cannot afford things like flood insurance coverage, which would give them more financial capacity to rebuild after a flood [56]. As such, when there is a constant threat of recurrent natural disasters such as hurricanes, it can lead to feelings of insecurity, worry, and uncertainty, and this can have a negative impact on mental health and wellbeing. Hence, it is critical to adopt deconstruction methods in post-disaster recovery to recover salvage materials that could be reused or recycled in low-income housing construction for underprivileged communities that cannot afford new building materials for reconstruction.

Building deconstruction is one of the most effective solutions for reducing: (1) the amount of disaster debris disposed of in the landfill; (2) CO_2 emissions; and (3) the exploitation of natural resources for faster reconstruction [57]. Denhart (2009b) highlighted that Mercy Corps recovered 32,000 board feet of reusable lumber through deconstruction for redirecting it into the marketplace in the aftermath of Hurricane Katrina [22]. The study clearly indicated that it is possible to recover salvage materials from buildings impacted by hurricanes if proper deconstruction strategies are implemented for the recovery of materials. McCarthy and Glekas (2020) also highlighted that deconstruction is an effective approach to preserve heritage by rethinking the idea of waste and promoting sustainable community development [58]. The study also highlighted that two buildings were deconstructed after Hurricane Irma impact in Savannah, Georgia. Using a building deconstruction approach, the project team recovered 65 tons of salvage materials, which amounts to approximately 60% of the materials diverted from the landfill for reuse. These two case studies show that building deconstruction post-disaster is feasible, and the circular economy resilience framework proposed in this study facilitates stakeholders in easily adopting deconstruction approaches by considering the strategies recommended in the framework.

The recovery efforts during post-disaster reconstruction often focus on the traditional linear economic model of demolition and disposal of disaster debris in the landfill. Such an approach is unsustainable and reduces the adaptive capacity of a community to respond effectively to natural disasters. Hence, this study introduces the novel concept of circular economy resilience to design and implement sustainable practices that not only reduce the negative impacts of disruptions during a natural disaster but also create opportunities for innovation and growth. Circular economy resilience can be referred to as the ability of a system, organization, or community to withstand and recover effectively from natural disaster impact while minimizing waste and maximizing resource efficiency [59,60]. This study also highlights the importance of assessing post-disaster recovery sites for the feasibility of building deconstruction, such that salvage materials can be recovered and reused in the reconstruction process. Additionally, by promoting deconstruction practices, the study encourages the reduction of embodied energy in the production of new materials by substituting recovered existing materials as a resource for reconstruction.

5. Limitations and Future Work

This study utilizes a dataset from Hurricane Irma to develop a regression model with relatively high accuracy. Future work will focus on validating the model by utilizing the dataset from the most recent hurricane to compare predicted building reusability with actual reusability. The reconnaissance dataset used in this study also did not include information related to deconstruction feasibility for recovery of salvage materials. Hence, future studies can focus on data collection during reconnaissance of building components with an emphasis on building deconstruction feasibility and the reuse potential of building materials. The availability of such a dataset would significantly accelerate the adoption of circular economy practices post-disaster.

6. Conclusions

The grand challenges of post-disaster recovery, such as a lack of resources for reconstruction and the generation of a significant amount of waste, among others, can be addressed through circular economy resilience. The existing literature lacks a comprehensive framework addressing the integration of resource-efficient approaches to effective disaster recovery. This study has addressed this literature gap, and the following conclusions were drawn.

6.1. Increase in Extensive Damages

The thematic analysis of hurricane reconnaissance reports indicated that the intensity of hurricanes has significantly increased over the years. Consequently, there is a significant increase in building damage, and a large number of buildings are either completely destroyed or have major damage, whereas very few buildings have minor damage. Such extensive damage leads to demolition of the buildings, and the building components or materials are diverted to landfills for faster recovery. Such traditional practices and policies have environmental implications such as land pollution, an increase in greenhouse gas emissions, and impacts on the health and wellbeing of disaster-prone communities.

6.2. Gradient-Boosting Regression Model

This study made a comparison between the most widely used supervised machine-learning algorithms to identify the algorithm capable of predicting building reusability with the highest accuracy. Based on the results, the gradient-boosting regression model had the highest accuracy of 66.7%, indicating that the model has a moderate predictive power. The study also developed a feature importance plot for the gradient-boosting regression model, and the results indicated that roof structure damage has the highest feature importance value, whereas wall structure damage has the lowest feature importance value. This result indicated that less damage to the roof structure may significantly increase the reusability potential of buildings in the aftermath of hurricane impact.

6.3. Circular Economy Resilience Framework

The proposed circular economy resilience framework has several practical applications. First, circular economy resilience practices help to reduce the loss of culturally significant structures and to recover salvage architectural and historical building materials for heritage preservation. The study also recommends solutions such as utilizing deconstruction methods, constructing buildings with homogeneity and less hazardous materials, and a plan for easier disassembly of building components, among others, to maximize circular economy practices. In addition, the construction workforce needs to be trained and educated about proper deconstruction and recycling or reuse practices. These practices can potentially accelerate the deconstruction schedule and encourage government officials and international organizations to invest financial resources in circular economy practices during the post-disaster recovery phase. The proposed framework also reduces the environmental footprint of post-disaster reconstruction through the conservation of resources and a reduction in energy consumption associated with manufacturing new materials. Consequently, the adoption of such practices would promote resource efficiency and support climate resilience by reducing the emission of greenhouse gases that are generated during the extraction and manufacturing of new materials.

The findings of the study contribute to disaster management and sustainable construction bodies of knowledge by highlighting the impact of different factors on building reusability and creating awareness of circular economy practices among construction stakeholders and policymakers. The novel contribution of this research is the provision of a data-driven and systematic approach to recommending sustainable strategies for post-disaster recovery by using a three-step research methodology that combines thematic analysis of reconnaissance reports, statistical analysis of datasets through machine-learning techniques, and insights from a substantial number of interviews.

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