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A comprehensive framework towards safe disposal of construction and demolition waste: The case of Egypt

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Abstract Construction and demolition waste (CDW), produced at various stages of construction projects, is a major problem for the construction industry. This waste has led to an international issue that is widespread and enduring. This research used a quantitative method in two stages to suggest workable options to fix this significant problem. An online survey of Egyptian construction industry professionals was conducted during the first round to gauge how three key factors affected the safe disposal of CDW (SDCDW). Management of route, collection, and transportation (MRCT), determination of illegal waste dumping sites (DIWDS), and construction waste tracking and scheduling (CWTS) are the three main factors. The development of a comprehensive framework for SDCDW, in support of Egypt's vision 2030, involved multivariate statistical analysis using the structural equation modelling (SEM) method in the second stage. The findings showed that these three factors had a favourable impact on SDCDW in Egypt. This was evidenced through mentioning the acceptable effect sizes of these three factors towards SDCDW; where MRCT showed moderate effect towards SDCDW with a value of 0.16, CWTS showed small effect towards SDCDW with a value of 0.137, and DIWDS showed small effect towards SDCDW with a value of 0.052.The study also discovered that MRCT is more effective in treating SDCDW with a model path coefficient of 0.383. However, DIWDS is the least effective when it comes to SDCDW with a model path coefficient of 0.191. In support of Egypt's Vision 2030, this paper makes concrete suggestions for the government and the construction sector regarding the safe disposal of CDW.

1. Introduction

The construction industry is one of the crucial industries supporting nations' economic and social advancement. According

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to a report released by the World Bank in 2012, solid waste (SW) will increase from 1.3 billion tonnes to 2.2 billion tonnes by 2025[29]. About half of the annual SW created comprises construction and demolition waste (CDW). Transparency Market Research forecasted a significant increase in CDW quantities created during the ensuing years in 2017. Waste in construction materials is a significant problem for the Egyptian construction industry [14;9] Construction industry sustainability is critically threatened by the resource waste, environmental damage, and ecological devastation caused by CDW [5,8]. It is becoming a severe problem since there are insufficient disposal facilities to handle the rising volumes of construction site waste. Due to a lack of regulated waste disposal sites, illegal dumping along local roadsides is rising. Toxic materials from this waste contaminate the land and drinking water, polluting the ecosystem and jeopardising the local population's health [9;25].

Additionally, the widespread practice of dumping and improperly disposing of CDW harms the environment and society. Illegal dumping and improper disposal of CDW are frequent practices in the MENA region, including Egypt. Such behaviour caused the solid waste issue to worsen, which in turn has numerous detrimental effects on the economy, society, and environment, constituting the triple bottom line of sustainability (TBL) [11–13]. The Sustainable Development Strategy (SDS) targets for Egypt 2030 are being implemented through massive development projects that the Egyptian government is making enormous efforts to carry out. However, the development of these massive projects produces a large amount of construction and demolition waste, which poses a serious obstacle to increasing sustainability.

Informally, at an unlicensed dumpsite close to the construction site that charges less than the authorised dumps, or at officially authorised public dumpsites, sorting dumpsites, debris dumpsites, or other locations. The inability to retrieve a sizable proportion of CDW from illegal dump sites is a pervasive problem [40]. Due to poor management, CDW is strewn on Egypt's roads and infrastructure. Furthermore, most landfills are hazardous and do not take enough precautions to prevent waste from self-igniting[10].

Even though there have been numerous studies aimed to enhance CDW management (CDWM) during the design and construction phases through the reduction and reuse of CDW, only a small portion of prior research has concentrated on offering solutions for ensuring the safe disposal of materials wastes using automation techniques, which has significantly contributed to the persistence of this issue to this day [30]. The Egyptian waste management law #202/2020 does not recommend or outline a methodology of disposal methods that incorporate automation techniques, even though it mandates the keeping of a record of all wastes, including construction and demolition wastes and methods of their disposal, in addition to considering safe disposal of wastes to be one of its obligations [30]. Therefore, this paper aims to examine the variables that affect the safe disposal of CDW in the Egyptian construction sector. This will significantly help the Egyptian construction industry safely dispose of CDW.

A theoretical framework for assuring the safe disposal of CDW (SDCDW) was developed by Ismail et al. [30].. This framework is primarily based on three factors that come from the categorisation of waste management processes shown in Ismail et al. [30] as follows: (1) management of route, collection, and transportation management; (2) determination of illegal waste dumping sites; and (3) construction waste tracking and scheduling. These factors make up the independent variables (IDVs) that are anticipated to directly impact the safe disposal of CDW as a dependent variable (DV). The primary goal of this study is to examine and comprehend the phenomena of SDCDW.

This study aims to investigate and provide a suitable and practical method to dispose of CDW in the Egyptian construction sector safely. In order to advance Egypt's Vision 2030, this goal will be accomplished by: (1) assessing the impact of the three variables that frequently lead to SDCDW in the Egyptian construction sector; and (2) creating a comprehensive framework to dispose of CDW in the construction sector properly. In order to achieve the aforementioned objectives, the study explains and describes the chosen research technique in the following section. The research outcomes are presented along with an explanation of the findings and results. Additionally, a road map is provided to depict the suggested comprehensive framework for the safe disposal of CDW in Egypt. The discussion concludes with conclusions and recommendations for the future.

2. Research methodology

An extensive analysis of the cause-and-effect relationships between the three aforementioned elements and SDCDW was essential to suggest a realistic strategy that aids the construction industry sector in safely disposing of CDW in Egypt. These characteristics, which comprise independent variables (IDVs), have a considerable impact on the SDCDW, which serves as the dependent variable (DV). The effect is denoted as "DV," while the cause is denoted as "IDV." The relationship between the values of the DV and IDVs is best described as interdependent since the value of the IDV affects the value of the DV. In this regard, researchers are frequently eager to comprehend and foresee how IDVs affect DV. IDV and DV are also evaluated and represented by indicators, or "constructs," items [16]. Daoud et al. [15] claimed that all indicators reflecting the same factor are believed to have equivalent weights and, as a result, are irrelevant to one another.

Each indicator has been given an initial code used throughout the data analysis process to provide a direct and proportional picture of the theoretical framework. Table 1 displays the IDVs, DV, related items, and corresponding codes. Fig. 1 shows the theoretical framework in detail. Fig. 1 shows the causal connection between the three IDVs and how it affects the safe disposal of CDW (SDCDW). Three hypotheses will be explored and established within the Egyptian construction sector, as illustrated in Fig. 1 of the theoretical framework. The goal of this study is to test and validate the null hypothesis (H0) (i.e., IDV possess no effect on the DV) versus the alternative hypothesis (Hn), which states that the IDV has a positive impact on the DV. In other words, the goal is to present enough evidence to support the alternative hypothesis Hn rather than the null hypothesis H0. As a result, the following are the alternative three proposed hypotheses (Hn):

- H_1: Management of route, collection and transportation has a positive effect on SDCDW.

Table 1 Components of the theoretical framework.

Construct (i.e., variable)		Type	Indicator (i.e., item)	Code	References
Management of route, collection, and transportation (MRCT)	GIS/for route management (GIS)	IDV	Surveying and computer storage of major waste collection sites	MRCT.GIS.1	[24,36;42,51]
			Detection of CDW illegal disposal sites	MRCT.GIS.2	
			Prediction of CDW waste disposal shortest paths	MRCT.GIS.3	
	GPS	IDV	Transportation of waste from waste generation sources to disposal sites	MRCT.GPS.1	
			Selection of shortest path transport route	MRCT.GPS.2	
			Monitoring of waste collection and disposal	MRCT.GPS.3	
			Tracking of waste transportation trucks	MRCT.GPS.4	
	Sensors (SENS)	IDV	Accurate control and high accuracy in CDW quantity collection and safe disposal	MRCT.SENS.1	
			Automatic calculation of the quantity of CDW at the start of the disposal trip till the end of the disposal trip to ensure safe disposal of the whole CDW quantity	MRCT.SENS.2	
Determination of illegal waste dumping sites (DIWDS)	Image processing (IP)	IDV	Detection of more illegal dumping sites through image processing	DIWDS.IP.1	
	GIS/ for illegal waste disposal sites determination (GIS)	IDV	Surveying and computer storage of all illegal waste dumping sites	DIWDS.GIS.1	
			Detection of more possible safe dumping sites	DIWDS.GIS.2	
Construction waste tracking & scheduling	RFID	IDV	Tracking and control of wastes from the generation site to the safe disposal site	CWTS.RFID.1	
	Rule-based reasoning (RBR)	IDV	Waste tracking and scheduling optimisation through taking intelligent decisions based on previously collected data about shortest transportation paths and efficient planning of waste disposal activities	CWTS.RBR.1	
Safe disposal of CDW (SDCDW)		DV	Reduction of accumulation of CDW in illegal disposal sites	SDCDW.1	[37]
			Protection of the environment against pollution	SDCDW.2	
			Improve the life of citizens as a social aspect of sustainability	SDCDW.3	

- $H_{2:}$ Determination of illegal waste dumping sites has a positive effect on SDCDW.
- H_3: Construction waste tracking and scheduling have a positive effect on SDCDW.

An online survey was administered to a representative sample of construction professionals operating in Egypt at various levels and specialities to study the aforementioned cause-and-effect linkages within the construction industry. The survey technique is helpful when a researcher wishes to examine: (1) attitudes, opinions, and organisational practices; and (2) links between diverse variables, particularly cause-and-effect correlations [42]. As a result, the chosen strategy helped to collect comprehensive data using the right sample size, enabling a summary of the results. The method comprises several steps described in more detail in the subsections below.

2.1. Design of the survey questionnaire

The survey questionnaire was divided into three main sections. The purpose of the first segment is to gather generic data from responders. The applicability and effectiveness of each ICT or smart technology within the Egyptian construction sector are evaluated in section two. The respondents' level of agreement on reaching the results indicated in the questionnaire as a result of CDW safe disposal is also evaluated in section three.

All of the questionnaire's questions have predetermined answers. Three different types of five-point Likert scales were offered. Based on studies by Vagias [48] and Brown [4], the five-point Likert scale was developed and utilised as an assessment tool to measure respondents' feedback for each question First, the applicability of various Information and Communication Technology (ICT) solutions for specific areas of construction waste management that are supposed to affect the SDCDW in Egypt was assessed using the "applicability" Likert scale. On this scale, "1″ denotes "not applicable at all", while "5″ denotes "extremely applicable". On the other hand, the effectiveness of these various automation methods for SDCDW was evaluated using the "effectiveness" Likert scale. In this Likert scale, "1″ denotes "not effective at all ", and "5″ denotes "extremely effective." Finally, using the Likert scale with "1″ denoting "strongly disagree" and "5″ denoting "strongly agree," the degree of agreement on the predicted impacts of the safe disposal of CDW in Egypt toward a more sustainable building sector in Egypt was assessed.

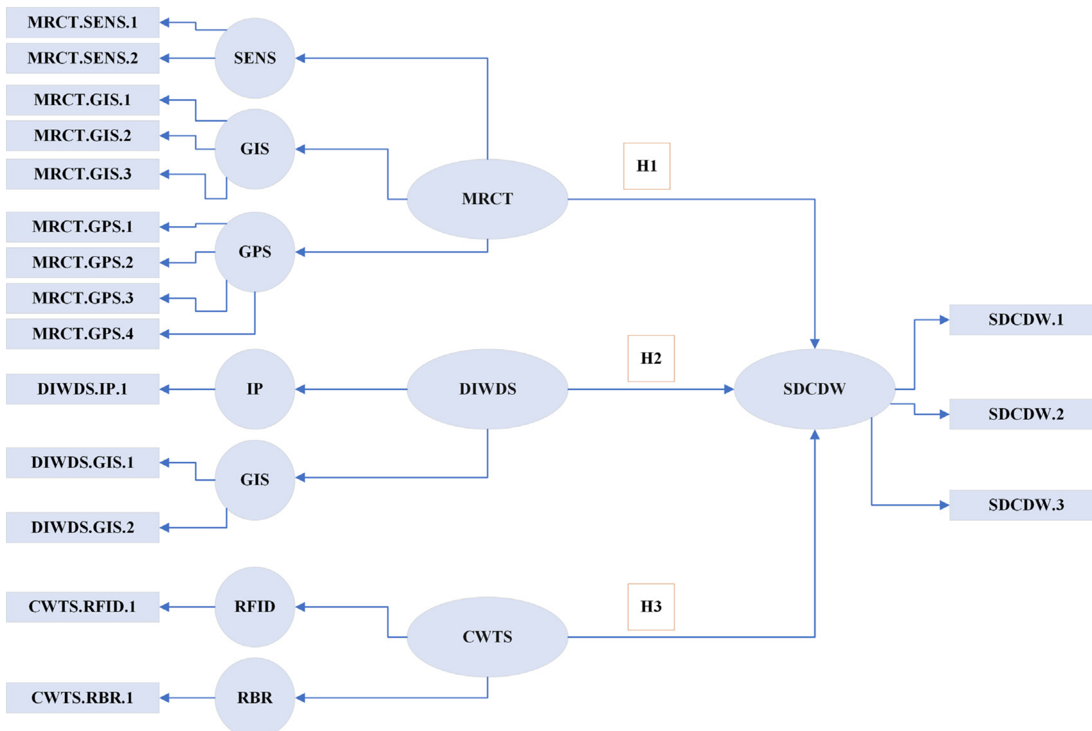

Fig. 1 The theoretical framework of the study.

2.2. Pilot survey

A preliminary pilot study was conducted to assess the survey questionnaire's use, clarity, and thoroughness [41]. A minimum sample size of 10 people is preferred for pilot testing [42]. The sample for this pilot test consisted of 26 individuals, 16 of whom are industry professionals, and the remaining 10 are academics with more than ten years of teaching, research, and industry experience. The creation of content and face validation resulted from piloting with the aforementioned expertise. The questionnaire was finished in an average of 15–20 min, based on comments from the respondents.

2.3. Sample size – Targeted participants

An unlimited number of academics and engineers with specialities in general civil engineering, particularly in construction engineering management, waste management, and sustainability disciplines, are taken into account for the sample size calculation in this study. The representative sample size was determined from the entire population using a SurveyMonkey sample size calculator (i.e., unlimited population). Enter the following three values into the calculator to determine the sample size: Population (empty because the population was unbounded), Confidence Level Percentage, and Margin of Error Percentage are the first three variables. The survey's margin of error, which is stated as a percentage, demonstrates how much the sample mean's findings are likely to vary from the population's actual viewpoints (i.e., mean). The confidence level, expressed as a percentage, expresses how confident the researcher is that the population will choose an answer that fits within the confidence interval [10]. It is recommended that 95% is the greatest confidence level for survey research [10]. It was also suggested to have a confidence interval between 5% and 10%. With a 95% confidence level and an 8.5% confidence interval, 133 respondents were needed as the sample size for this study. There were 146 replies, which is more than the required sample size.

3. Results and discussion

The structural equation modelling (SEM) method was used with the SmartPLS 3.3.2 software to analyse the compiled data. SEM was used to test the three hypotheses and the theoretical framework. The SEM is a method for investigating relationships between IDVs and DVs in general linear models. These variables can be directly observed either as latent variables or as measured variables (i.e., indicators or items) (i.e., constructs). A postulated causal theoretical framework's explanation and validation are the main objectives of SEM. The SEM is a validation process that depends on the following two steps:

(1) The first stage is to carry out confirmatory factor analysis (CFA) of the measurement model to see how well the measured indicators match their relevant constructs; and.

(2) The second step entails putting the structural model into practice and testing the study hypotheses using path analysis.

Xiong et al. [50] claimed that SEM has been successfully reproduced for use in construction research and has been widely used in social science and psychology research. Kline [31] and Tenenhaus et al. [46] determined that the most practical method for investigations involving practical settings is the partial least squares (PLS) method of the SEM (PLS-SEM). This is mostly attributable to its problem-oriented methodology, which strives to offer workable solutions for problems that have been recognised. For models incorporating IDVs and DVs, a PLS-SEM analysis is a useful substitute for covariance-based SEM (CB-SEM) or regular least squares regression. Multicollinearity among IDVs can be handled by the PLS-SEM analysis, which also creates IDVs based on cross-products and more reliable predictions. It tests the data and path models simultaneously to generate more realistic assumptions [7,47].

As a result, the PLS-SEM approach is regarded as an effective substitute for the CB-SEM. Because SmartPLS 3.3.2 software offers the most widespread PLS-SEM method application, it was used to conduct the PLS-SEM study [17]. The following subsections present the outcomes of the PLS-SEM analysis and the theoretical framework's evaluation tests. The PLS-SEM effectively confirms and tests the theoretical underpinnings of numerous theories. The proposed comprehensive framework served as a road map for enhancing the current circumstance in Egypt. On the other hand, the relative importance index (RII) was utilised to rank the main elements impacting SDCDW in terms of their effectiveness after statistical analysis of the quantitative data from the online questionnaires. Sutanapong & Louangrath [45] claimed that using the mean and RII to explain, summarise, and visualise the acquired data in numerical and graphical representations reveals various patterns that emerge from the data and aids in the communication of important information.

3.1. Assessment of measurement models

The measurement models describe the link between the constructs and their indicators, also known as the outer models (i.e., items). In social science research, reflective measurement models are frequently utilised. Measurement models can either be formative or reflective. These models' indicators frequently show how the underlying construct has an impact. This indicates that the construct produces its indicators, and since all of the indicators measuring the construct are caused by the same construct, there must be a strong correlation between them. Additionally, all indicators measuring a particular construct must be interchangeable for the construct's interpretation to remain constant even if one indicator is removed and the reliability to remain acceptable. (J. F. [18]. When evaluating reflective measurement models in PLS-SEM, internal consistency, reliability, convergent validity, and discriminant validity must be considered. The guidelines and road map for evaluating the reflective measurement model are summarised in Table 2. Once the measurement model's validity and reliability have been proven, the structural model will be assessed. The measurement model's validity and reliability are covered in the following subsections.

Table 2 Criteria of reflective measurement model assessment. Source: [17]; J. F. [20,23,26,33,50].

Evaluation Items	Measurement Items	Fitting Criteria
Reflective Measurement Model		
Internal consistency reliability	Composite reliability	> 0.70
Convergent validity	Indicator loadings	> 0.70
	Average Variance Extracted (AVE)	> 0.50
Discriminant validity	Hetrotrait-Monotrait (HTMT) ratio	< 0.85 – 0.90

3.1.1. Internal consistency reliability

A construct's internal consistency reliability determines whether all of the indicators linked to it are measured[35]. Because Cronbach's alpha has several drawbacks, it is advised to employ a different internal consistency test, such as composite reliability [19]. For instance, the top boundaries of Cronbach's alpha, which measure the reliability of random patterns, are not perfect[36,49]. In contrast, composite reliability evaluates the internal consistency while considering each indicator's specific outer loading. The reliability estimations are substantially larger because composite reliability overestimates internal consistency reliability. It is typically explained similarly to Cronbach's alpha, where the composite reliability spans from 0 to 1, and larger numbers denote higher levels of reliability [19].

For exploratory research, composite reliability values between 0.60 and 0.70 are sufficient, according to [19]; however, values between 0.70 and 0.90 indicate good reliability and internal consistency level for advanced stages of study (i.e., explanatory research). Following the aforementioned criteria, the admissible composite reliability value above 0.70 was considered for this investigation. To measure the lower and upper bound, this research has employed a mixed technique using Cronbach's alpha and the composite reliability [19]. Therefore, using the calculations offered by SmartPLS 3.3.2, the reliability was assessed for each construct. Cronbach's alpha and composite reliability values are shown in Table 3 for each construct. All of the constructs have reliability ratings of more than 0.70, indicating strong dependability and substantial internal consistency.

3.1.2. Convergent validity

Convergent validity, according to Joe F. Hair et al. [21], evaluates the correlation between variables chosen to measure the same construct. The outer loadings of the items and the average variance extracted (AVE) are frequently used to evaluate the convergent validity of reflective measurement models. Not < 0.70 is the acceptable minimum significant outer loading [21]. AVE represents the grand mean of the squared loadings of the indicators measuring a construct. A construct's AVE must be at least 0.50 to be considered remarkable [21]. All of

Table 3 Measurement model analysis' reliability.

Construct	Cronbach's Alpha	rho_A	Composite Reliability
Construction waste tracking & scheduling	0.861	0.861	0.935
Determination of illegal waste dumping sites	0.759	0.775	0.861
Management of route, collection, and transportation	0.88	0.883	0.904
Safe disposal	0.789	0.817	0.876

the constructs in Fig. 2 had AVE ratings better than 0.50. Fig. 2 shows the outer loadings for each construct, whereas Table 4 shows the AVE values for each construct. All reflective measurement models' values of outside loadings were discovered to be higher than the 0.7 cut-off value, demonstrating the high level of indicator dependability.

3.1.3. Discriminant validity

After confirming the convergent validity, Jörg Henseler et al. [26]suggested evaluating the discriminant validity using the Hetrotrait-Monotrait (HTMT) ratio. A construct's distinction from other constructs is what determines its discriminant validity. The ratio of between-trait correlations to within-trait correlations is referred to as HTMT. Concerning the average of the correlations of indicators inside a single construct, it is the average of the correlations of indicators across constructs assessing various phenomena[26]. The value of HTMT should be < 0.90 if the model structures are conceptually similar. In contrast, when the value of HTMT is smaller than 0.85, the model structures are conceptually separate. As all of the constructs have HTMT values below the specified threshold, the discriminant validity was performed using the aforementioned principles. The HTMT values for the constructs are shown in Table 5.

3.2. Assessment of structural model

The structural model, often known as the inner model, depicts the relationships that now exist between the structures [3,21]. The structural model was created after a thorough analysis of the literature, and the constructs' placement within the model had to be determined by theory, logic, or observations [26]. Cause-and-effect relationships are what the relationships in the study's structural model are thought to be. Direct correlations between the factors in which one component predicts the other is known as causal links or relationships. The theoretical framework included a description of the structural model for this investigation.

The structural model should be evaluated after determining the measurement models' validity and reliability. The structural model's evaluation includes determining its ability to predict outcomes and the links between its many aspects (J. F. [20,27,28]. Several researchers provided guidelines for evaluating and reporting the structural model, which includes multicollinearity, path coefficients, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and goodness of fit (**GoF**). Summary of the utilised criteria in this study to evaluate the structural model is shown in Table 6. According to review studies [2,19], [22,21,39,38] of the PLS-SEM, these criteria are frequently reported by researchers while analysing the structural model. Table 6 below lists these evaluations' standards, recommendations, and results in the subsequent subsections.

3.2.1. Multicollinearity

It happens when a large correlation between two constructs exists, resulting in interpretation issues. In case of more than two constructs are included, it refers to collinearity or multi-

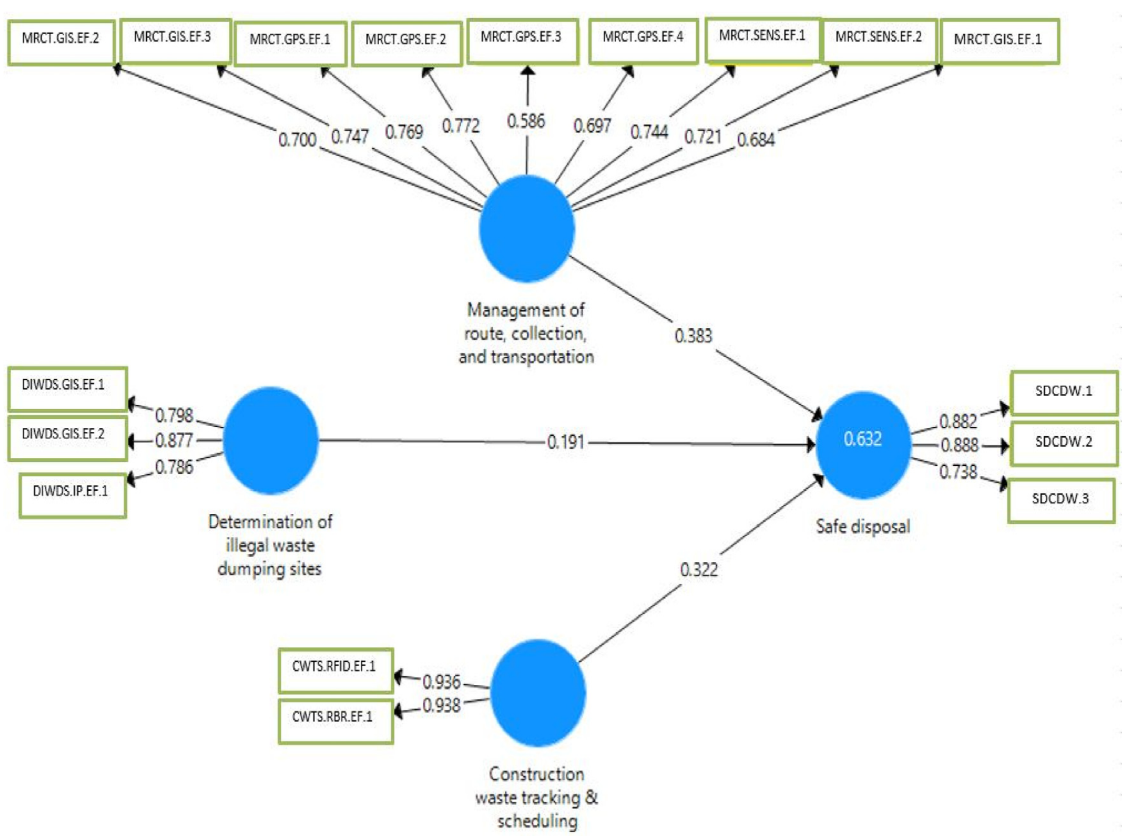

Fig. 2 Outer loadings and AVE for different constructs in the research model.

Table 4 Average Variance Extracted (AVE) of different constructs.

Construct	Construction waste tracking & scheduling	Determination of illegal waste dumping sites	Management of route, collection, and transportation	Safe disposal
AVE	0.878	0.674	0.512	0.704

Table 5 HTMT values.

Construct	Construction waste tracking & scheduling	Determination of illegal waste dumping sites	Management of route, collection, and transportation
Determination of illegal waste dumping sites	0.719		
Management of route, collection, and transportation	0.801	0.824	
Safe disposal	0.839	0.824	0.868

Table 6 Criteria for assessing the structural model. . Source: [1,2,6,26,28,33,35,45]

Criteria	Guidelines
Multicollinearity	**VIF** < 5
Path coefficients	At a significance level = 5%; ***P*-value** ≤ 0.05 & ***t*-value** ≥ 1.96, significant relationship.
Coefficient of determination ($\boldsymbol{R}^2$)	$\boldsymbol{R}^2$ < 0.19, unacceptable predictive accuracy; $\boldsymbol{R}^2$ = 0.19 – 0.33, small predictive accuracy; $\boldsymbol{R}^2$ = 0.33 – 0.67, moderate predictive accuracy; $\boldsymbol{R}^2$ ≥ 0.67, high predictive accuracy.
Effect size (f^2)	$\boldsymbol{f}^2$ < 0.02, no effect; $\boldsymbol{f}^2$ = 0.02 – 0.15, small effect; $\boldsymbol{f}^2$ = 0.15 – 0.35, moderate effect; $\boldsymbol{f}^2$ ≥ 0.35, high effect.
Cross-validated redundancy ($\boldsymbol{Q}^2$)	predictive relevance using blindfolding; $\boldsymbol{Q}^2$ > 0
Goodness of fit (**GoF**)	**GoF** < 0.1, no fit; **GoF** = 0.1 – 0.25, small fit; GoF = 0.25 – 0.36, medium fit; **GoF** ≥ 0.36, large fit.

collinearity. Collinearity is capable of being tested by utilization of the variance inflation factor (VIF), that is got by the division of one by tolerance referring to the variance illustrated by one independent construct not explained by the other independent constructs [3;19]. The value of VIF as 5 or higher indicates high collinearity. Table 7 shows that the VIF values for all constructs are below the cut-off point, proving that the collinearity between independent constructs has no existence.

3.2.2. Path coefficients

They indicate the estimates of the possible relationships between the model's constructs (J. F. [21]. They range from + 1 to −1, where + 1 indicates a relationship described as strongly positive, 0 means the absence or weakness of the relationship, and −1 indicates a relationship described as strong negative [17].

Table 7 Variance inflation factors for IDVs.

Construct	VIF	Remark
Construction waste tracking & scheduling	2.061	The collinearity problem does not exist
Determination of illegal waste dumping sites	1.925	
Management of route, collection, and transportation	2.498	

The hypothesis was tested to understand the size, signs, and statistical significance of the predicted path coefficients between the constructs. Path coefficients of higher values indicate stronger effects between the predictor and predicted variables. The supposed relationships' significance has been reached by measurement of the *p*-values' significance for each path with outset $p < 0.05$, $p < 0.01$, $p < 0.001$ utilized to examine the path coefficient estimations' significance (J. F. [21]. Then, the inferences were figured out for all hypotheses based on the *p*-values' significance at the conventional levels mentioned above. Inference of hypotheses and *p*-values, in addition to the confidence level for each estimate, are shown in Table 8 and Fig. 3.

The results of hypothesis testing in Table 8 and Fig. 3 showed that *management of route, collection, and transportation* construct resulted in a significant direct positive effect on *Safe disposal* construct since ($\beta = 0.383, t = 3.886, P < 0.001, 95\% CI \mathrm{for} \beta = [0.187, 0.563]$), consequently, the first hypothesis is confirmed. *Determination of illegal waste dumping sites* yielded a significant direct positive effect on *Safe disposal* construct since ($\beta = 0.191, t = 2.594, P < 0.01,\ 95\% CI \mathrm{for} \beta = [0.055, 0.345]$), consequently, the second hypothesis is proved. Finally, *Construction waste tracking & scheduling* revealed a significant direct positive effect on *Safe disposal* since ($\beta = 0.322, t = 3.133, P < 0.01, 95\% CI \mathrm{for} \beta = [0.127, 0.52]$), consequently, the third hypothesis is also confirmed.

3.2.3. Coefficient of Determination ($\boldsymbol{R}^2$)

The determination coefficient indicates the independent variables' effect on the latent dependent variables (J. F. [22], which represents one of the structural model's quality measures (J. F. [21]. The estimates of R^2 range from 0 to 1, where 0 indicates a variance described as low explained and 1 indicates a variance described as high explained. Researchers utilized various cut-offs of R^2 value. Table 9 shows the values of R2 and associated R2adj for the DV. R2 of *Safe disposal* were 0.632, meaning that approximately 63% of the variations in *Safe disposal* were explained by the variation in the independent variables, which is considered a moderate value.

3.2.4. Effect size ($\boldsymbol{f}^2$)

The effect size (f^2) quantifies how much an exogenous construct (such as IDV) will modify the model's R^2 value and have

Table 8 Model path coefficients.

Hypothesis		B	t-value	P-value	95% CI for B		Remark
					LL	UL	
H1	Management of route, collection, and transportation -> Safe disposal	0.383	3.886	0.000***	0.187	0.563	Accepted
H2	Determination of illegal waste dumping sites -> Safe disposal	0.191	2.594	0.01**	0.055	0.345	Accepted
H3	Construction waste tracking & scheduling -> Safe disposal	0.322	3.133	0.002**	0.127	0.52	Accepted

***P < 0.001; **P < 0.01; LL = Lower Limit; UL = Upper Limit; CI = Confidence Interval.

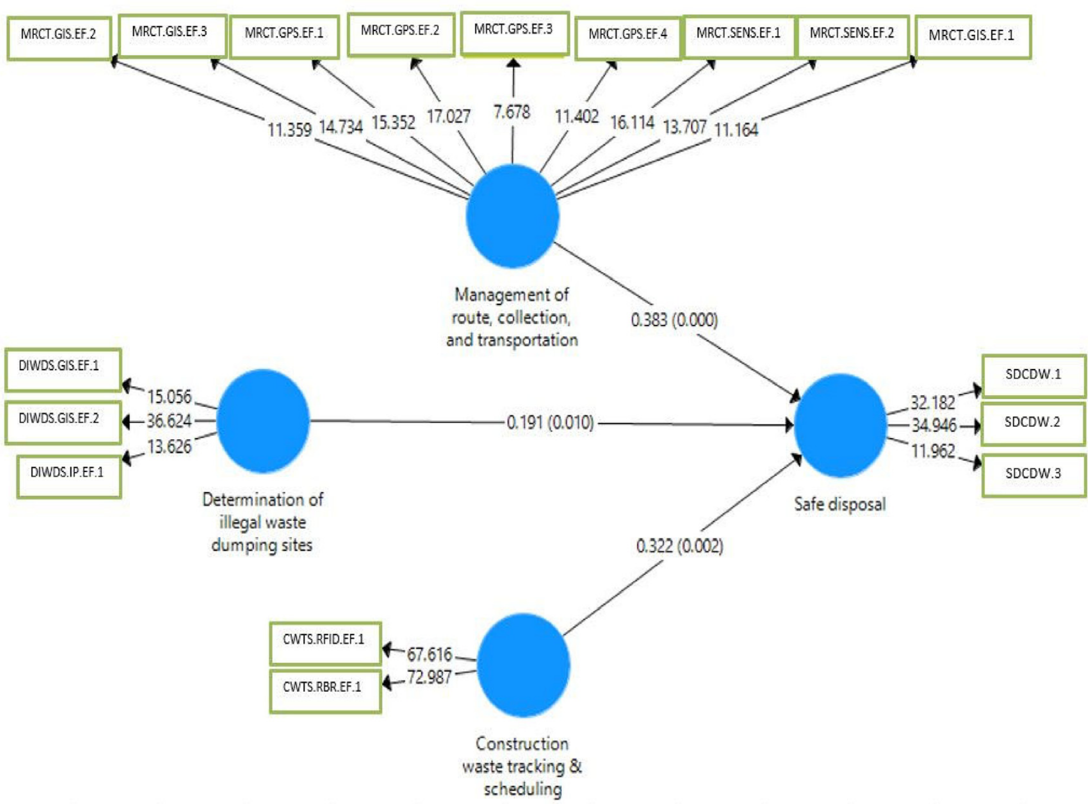

Fig. 3 **Model** path coefficients with corresponding p-values and R^2 $_{\text{adj}}$ value of DV.

Table 9 Values of R^2 and associated R^2_{adj} for the DV.

Dependent Variable	R Square	R Square Adjusted	Remark
Safe disposal	0.632	0.624	Moderate

an impact on the endogenous construct [19]. The values of f^2 are calculated using the **SmartPLS©** software. If a construct's f^2 value is between 0.02 and 0.15, it is regarded to have a minor effect. If it is between 0.15 and 0.35, it is considered to have a medium effect. If it is larger than 0.35, it is considered to have a significant effect. Joe F. Hair et al. [18] state that a construct with a f^2 value of < 0.02 indicates that it has no impact on the endogenous construct. Table 10 represents the effect size of the constructs.

Results illustrate that *Construction waste tracking & scheduling* and *determination of illegal waste dumping sites* have a small effect in the model, while *management of route, collection, and transportation* have a medium effect.

Table 10 The effect size of IDVs.

Construct	Safe disposal	Remark
Construction waste tracking & scheduling	0.137	Small
Determination of illegal waste dumping sites	0.052	Small
Management of route, collection, and transportation	0.16	Moderate

3.2.5. *Predictive relevance (Q^2)*

Predictive relevance Q^2 value refers to the out-of-sample predictive power of the model. When considering a model to have predictive power, data not used in the model estimation can be accurately estimated. Q^2 value is achieved through doing a blindfolding sequence. Prior to the run of this sequence, a distance of omission (D) has to be identified. Researchers suggest the specification of between 5 and 10 to be considered as D while being cautious that no integer would be produced when the sample size undergoes division by the selected D. The distance of omission means that while the run of the blindfolding sequence, every point of data referred as $\times$ of the items will be removed then estimated, with $\times$ being the specified D value. A D of 5 means that about 20% of the data points have been omitted per blindfolding round. Similarly, a D of 10 indicates that about 10% of the data points were omitted per blindfolding round. An endogenous construct's Q^2 value larger than 0 indicates the model's predictive relevance for this construct. A distance of omission of 7 was chosen for the predictive power of the model examination [19]. Table 11 shows Q^2 results derived from the test. Values of Q^2 are higher than 0, so this leads to the conclusion that the research model has a predictive relevance described as good.

3.2.6. Goodness of fit of the model

Goodness of Fit (GoF) as a worldwide fit indicator was suggested by [46]; it gives the value of the geometric mean of both:

Table 11 Predictive relevance.

Construct	SSO	SSE	Q² "=1-SSE/SSO"
Construction waste tracking & scheduling	292	292	
Determination of illegal waste dumping sites	438	438	
Management of route, collection, and transportation	1314	1314	
Safe disposal	438	252.194	0.424

average R^2 and average variance extracted of the endogenous variables. GoF aims to take into consideration the research model at all stages, i.e. the measurement model and the structural model, with an emphasis on the overall model performance. The calculation of the index of GoF resulted in the following value

$$GOF = \sqrt{\overline{R^2} \times \overline{AVE}} = \sqrt{0.632 \times 0.692} = 0.661$$

The GoF criteria followed for whether GoF values are not acceptable, small, moderate, or high to be considered as a worldwide appropriate PLS model are shown in Table 6. Accordingly, as the value of the GoF is (0.661), The GoF model is big enough to be concluded and considered a sufficient valid global PLS model.

3.3. Effectiveness of different factors affecting C&DWR

The RII formula, first investigated by Olomolaiye et al. [34], was used to rank the factors' effectiveness. RII is derived using the equation below [44].

$$\mathbf{RII} = \frac{\sum W}{AN}$$

While "W" stands for the weights given to each item based on their effectiveness. It is rated on a scale of 1 to 5, with 1 denoting total ineffectiveness and 5 denoting tremendous effectiveness. On the other hand, "N" specifies the total number of respondents, and "A" denotes the highest weight on a rating scale, which in this study is 5 [32]. The range of the RII value is 0 to 1, with higher RII values indicating a factor's greater effectiveness than factors with lower RII scores. Therefore, the elements in each category are ranked according to their RII values, as illustrated in the next section and investigated in detail in the study carried out by Ismail et al. [30] The conclusions of the analysis include creating a road map to help policymakers and experts in the construction sector safely dispose of CDW in Egypt.

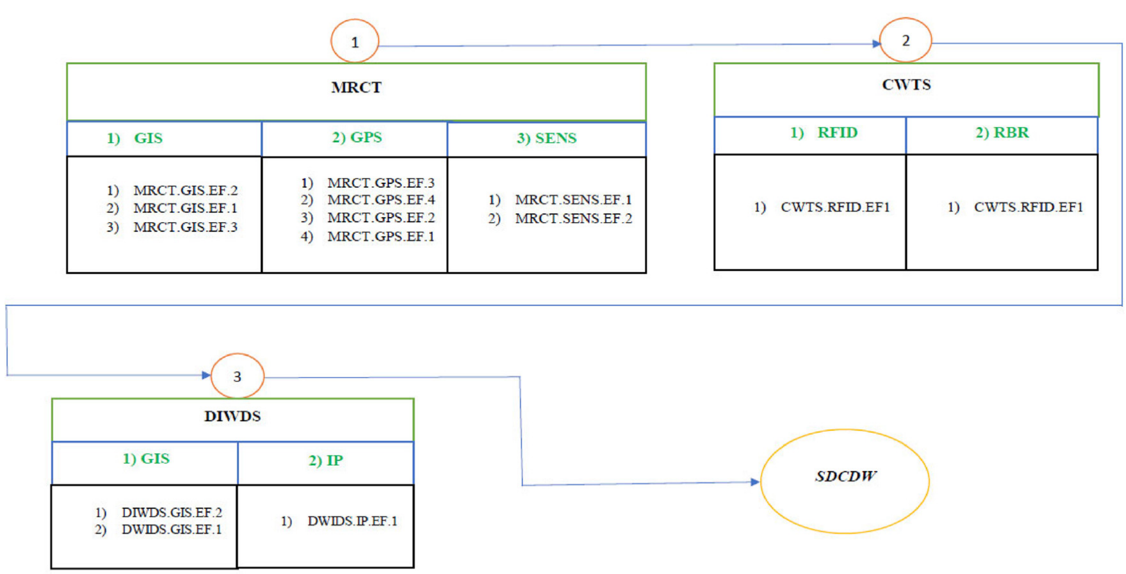

Fig. 4 Roadmap for implementing the comprehensive framework.

4. Roadmap for implementing the comprehensive framework in the Egyptian construction industry

Based on the findings from themodel path coefficients effect size analysis, and RII analysis for the effectiveness of various IDVs components (i.e., items), the following roadmap is presented to organise and prioritise the sequential application of the main aspects and their many components and metrics. The authors urge politicians and industry professionals to rigorously follow the suggested roadmap, which would surely help Egypt's construction industry dispose of CDW safely. The application of the various elements is arranged in this roadmap in descending order based on their weighting (i.e., model path coefficinets, effect size and importance), and the application of their measurements and components is arranged according to their level of importance as determined by RII analysis of their effectiveness. Depending on how much each IDV was weighted, the different IDVs were sorted in descending order. Fig. 4 shows the implementation roadmap for the comprehensive framework. According to their RII study, the three factors' components are listed in descending order in Fig. 4.

5. Conclusion

This study tackles the problem ofunsafe CDW disposal in Egypt. This is a major problem for the government and the construction industry because CDW can make up as much as 40% of the total cost of construction projects' components. Surprisingly, indiscriminate dumping dominates the way CDW is handled in Egypt, negatively impacting the environment and society. Accordingly, in addition to creating a cutting-edge comprehensive framework to aid policymakers and experts in the construction sector in the safe disposal of CDW in light of Egypt's vision 2030, this study provided an insightful strategy by examining the influence of three key criteria for SDCDW in Egypt. According to this study, "DIWDS" have the least impact on the safe disposal of CDW in Egypt while "MRCT" has the greatest impact. The created roadmap provides the path for the decision-makers to take simple actions to put the suggested comprehensive framework into practice. The proposed strategy will greatly help the government and the construction sector in Egypt's safe disposal of CDW. Future studies should focus on creating computer software applications that assist government agencies and business personnel in using the provided framework in construction projects in Egypt.

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.

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