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Integrated Framework Towards Construction Waste Reduction: The Case of Egypt

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Abstract

The construction industry is plagued with significant construction and demolition waste (C&DW) generated during various phases of construction projects. This waste has created a universal, pervasive, and enduring problem globally. To propose practical solutions to resolve this consequential issue, this research adopted a quantitative approach in two stages. The first stage involved an online survey, administered to 360 methodically selected construction organisations working in Egypt, to evaluate the impact of six main factors on C&DW reduction (C&DWR). The six main factors are as follows: (1) materials procurement measures (MPMR); (2) materials procurement models (MPMO); (3) green building practices (GBPR); (4) legislation (LG); (5) culture and behaviour (CB); and (6) awareness (AW). The second stage comprised multivariate statistical analysis via the structural equation modelling (SEM) approach to develop an integrated framework for C&DWR, to support Egypt's vision 2030. The results revealed that these six factors positively affect C&DWR in Egypt. Additionally, the study found that GBPR has the highest importance value of 0.293 and the highest performance rate of 92.169. However, CB has the second highest importance value of 0.238 whilst it has the lowest performance of 72.08 among the six factors. This paper proposes practical recommendations for the government and the construction sector to reduce the C&DW in support of Egypt's Vision 2030.

Keywords Construction and demolition waste · Waste reduction · Built environment · Sustainability · Structural equation modelling · Egypt

1 Introduction

The construction sector is one of the most significant contributors to a nation's growth from social and economic aspects, whereby it raises the living standards of a community [1, 2]. It entails the development of socioeconomic projects and infrastructure such as roads, hospitals, schools and universities for the community. Unsurprisingly, construction and demolition waste (C&DW) is becoming a global problem [3]. According to Hoornweg et al. [4], the

World Bank predicts that the amount of solid waste (SW) created globally will increase from 1.3 billion tonnes in 2015 to 2.2 billion tonnes in 2025. C&DW accounts for more than 50% of SW worldwide annually [5, 6]. According to a study published in 2017 by Transparency Market Research, the amount of C&DW produced will increase considerably in the future [6]. In fact, the improper disposal of C&DW is a prevalent practice globally and has a detrimental effect on society and the environment [7, 8]. Unquestionably, stochastic disposal is the most prevalent approach for handling C&DW in the Middle East and North Africa (MENA), including Egypt [9–14].

The United Nations Environment Programme (UNEP) [9] and Memon et al. [15] determined that the majority of dumping sites are hazardous and lack sufficient precautions to prevent waste from self-ignition and environmental contamination. Therefore, C&DW biodegradation in landfills generates significant health and environmental problems [16–18]. These illegal dumping practices have

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compounded the problem of solid waste, resulting in severe negative consequences on the environment, society, and economy, which are the pillars or triple bottom line (TBL) of sustainability [9–14, 19]. C&DW concerns need immediate action to resolve this situation in the MENA. The construction industry in Egypt is not an exception, mainly owing to the severe challenge posed by the improper management of construction waste [20]. According to Shamseldin [21], the cost of C&DW for any construction project should not exceed 4% of the total cost of materials. Surprisingly, 40% of total construction material costs in Egypt are wasted, representing around 16% of total construction costs for major projects in Egypt [21].

Undoubtedly, inadequate C&DW management (C&DWM) has a negative impact on the construction industry's efficiency, effectiveness, value, and profitability [22]. Within this context, Memon et al. [15], Park et al. [23], and Jalaei et al. [24] have claimed that the C&DW has a detrimental impact on the national economy and the TBL of sustainability. According to Caldas et al. [25], construction equipment and materials account for 50% to 60% of total project expenses, which are inextricably linked and significantly impact 80% of the project's schedule. Daoud et al. [26–31] conducted thorough research on C&DW concerns in Egypt, highlighting numerous factors that led to the reduction of C&DW in Egypt. These factors serve as the foundation for the theoretical framework established in this research. The conducted comprehensive literature review found that the proposed sustainable framework solution primarily depends on six major factors, including several sub-factors. The six factors are as follows: (1) materials procurement measures (MPMR); (2) materials procurement models (MPMO); (3) green building practices (GBPR); (4) legislation (LG); (5) culture and behaviour (CB); and (6) awareness (AW) [26–31].

In recent decades, research on C&DWM has analysed many approaches to minimise waste during the design and construction phases, but with less emphasis on minimising waste during the materials procurement stage [32]. Zeb et al. (2015) [33] have defined materials procurement as “purchasing of materials needed for execution of a project. Procurement is organizing the purchasing and scheduling delivery of materials to the suppliers”. According to Kamalaeaswari and Vedhajanani (2015) [28], organising material purchases and delivery timing is critical to obtaining construction materials of high standards concerning quality, quantity, pricing, location, and time. One of the primary causes of C&DW generation (C&DWG) is inefficient materials procurement, which impacts the project's overall cost [34, 35]. Ajayi et al. (2017a) [32] also reported that procurement of materials impacts 50% of the

entire project cost. Furthermore, Fadiya et al. (2014) [36] reported that the inefficient procurement of materials contributes up to 11.2% of total C&DWG. Waste-efficient procurement of materials, which constitutes a significant relationship between the design and construction phases, is essential to C&DW reduction (C&DWR) and cost reduction. Waste-efficient materials procurement practices include materials procurement measures and models for C&DWR and the adoption of green materials included in green building rating systems (GBRSs) [26, 27]. Due to the prevalence of “dumping” as the prevailing practice and the only available method for dealing with C&DW, the approaches mentioned above are seldom used within Egypt's construction industry [11, 16].

Moreover, Daoud et al. (2020b) [28] extensively researched SW and C&DW issues in the MENA area and Egypt. In addition to the waste-efficient materials procurement practices, it has been observed that external variables influence C&DWR; legislation, awareness, culture and behaviour. These factors play a crucial role in reducing C&DW via a set of specified actions that must be implemented within a framework for C&DWR. Daoud et al. (2020b) [28] reported that the Egyptian construction industry is poorly regulated because it suffers from a remarkable lack of waste-efficient legislation, improper culture, inappropriate behaviour, and a low level of awareness of the C&DW issue, which together amplifies the C&DW problem.

This research aims to investigate and propose the most appropriate and effective approach for minimising C&DW within the Egyptian construction industry. This aim will be achieved by: (1) evaluating the effect of the six factors that tend to result in C&DWR within the Egyptian construction sector; and (2) introducing an integrated framework to eliminate C&DW in the Egyptian construction sector to boost Egypt's Vision 2030. To that end, the study discusses and outlines the adopted research methodology used in attaining the abovementioned objectives in the following section. The results and findings are explained with the outcomes of the research presented. Moreover, the proposed integrated framework for reducing C&DW in Egypt is illustrated as a roadmap. Finally, conclusions and future recommendations are discussed.

2 Research Methodology

To propose a practical approach that assists policymakers and the construction industry sector in reducing C&DW in Egypt, an in-depth investigation of the cause-and-effect relationship between each of the six above-mentioned factors and C&DWR was paramount, taking into account the specific characteristics of the Egyptian construction

industry. These factors significantly impact the C&DWR, constituting independent variables (IDVs), whereas C&DWR represents the dependent variable (DV). The cause is referred to as “IDV”, while the effect is referred to as “DV” [37]. The value of IDV influences the value of DV; hence, the connection between the DV and IDVs is best characterised as interdependent. In this sense, researchers are often interested in understanding and anticipating the influence of IDVs on DV [37]. Indicators (i.e. items) are also used to measure and depict IDV and DV, referred to as “constructs”. Daoud et al. [38] claimed that all indicators reflecting the same factor should have equivalent weights and, as a result, are irrelevant to one another.

For a direct and proportional depiction of the theoretical framework, each indicator has been assigned an initial code utilised at a later stage within the analysis of data, in which the IDVs, DV, related items, and the corresponding codes are investigated in more depth by Daoud et al. [31]. The theoretical framework is illustrated in Fig. 1. Figure 1 depicts the cause-and-effect relationship for each of the six light blue ellipse-shaped factors and their influence on reducing C&DW. As shown in Fig. 1, the theoretical framework comprises six hypotheses to be investigated and established within the Egyptian construction sector. This research endeavours to test and validate the alternative hypotheses (H_n) (i.e. there exists a positive effect of the IDV on the DV) against the null hypotheses (H_0) (i.e. IDV possess no effect on the DV). In other words, the objective is to demonstrate sufficient evidence to reject the null

hypothesis H_0 in favour of the suggested alternative hypothesis H_n . Accordingly, the alternative six proposed hypotheses (H_n) are as follows:

- H_1 : waste-efficient materials procurement models have a positive effect on C&DWR.
- H_2 : waste-efficient materials procurement measures have a positive effect on C&DWR.
- H_3 : the green materials procurement approach of Green Building (GB) practices has a positive effect on C&DWR.
- H_4 : C&DWM legislation has a positive effect on C&DWR.
- H_5 : awareness has a positive effect on C&DWR.
- H_6 : culture and behaviour have a positive effect on C&DWR.

To investigate the aforementioned cause-and-effect relationships within the Egyptian construction sector, an online survey using Qualtrics was administered to a representative sample of construction professionals working at different levels and specialities in Egypt. The sample involved representatives from owners, consultants, supervisors, suppliers, government, and other parties directly or indirectly connected to the C&DWG. The online survey was deemed the most acceptable method as it is designed to study the relationship between cause and effect. In addition, Saunders et al. [39] asserted that the survey methodology contains unique characteristics that make it the preferred method for constructing reliable indices and verifiable data from field observations. The online survey is

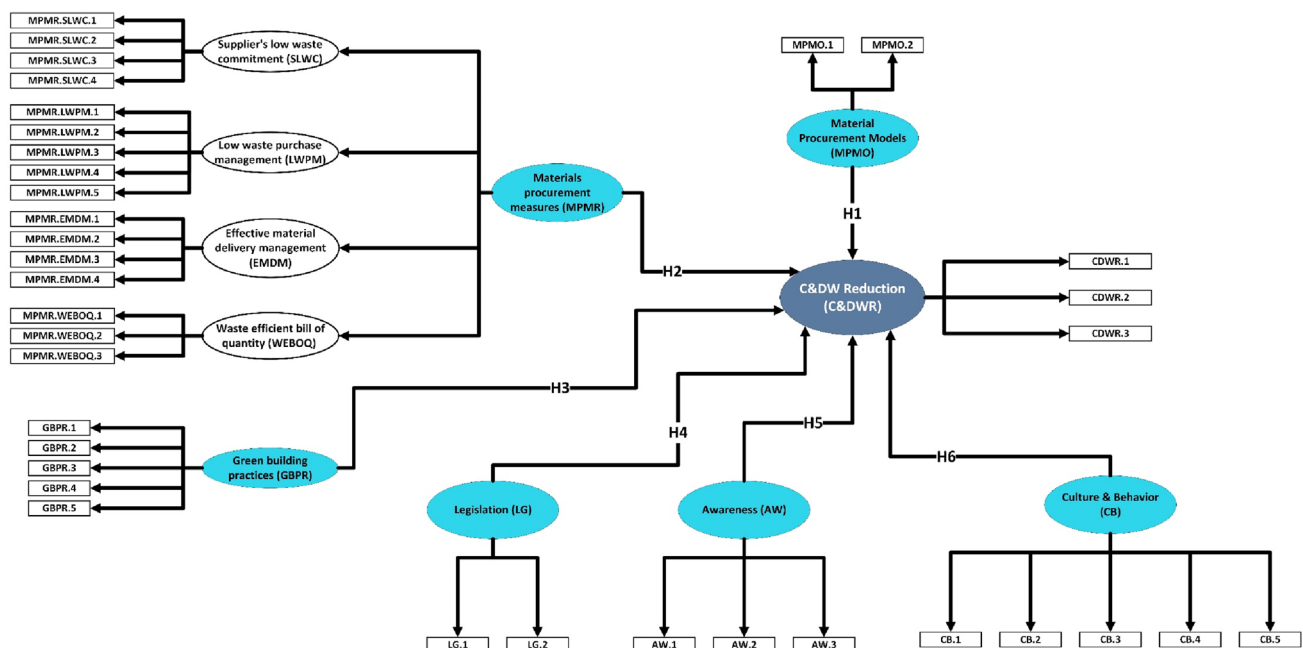


Fig. 1 The theoretical framework of the study

valuable in investigating the following aspects: (1) attitudes, beliefs, and organisational practices; and (2) the correlation between diverse variables, particularly for cause-and-effect relationships [39]. Consequently, the selected approach assisted in acquiring in-depth data utilising the proper sample size, allowing for a summary of the findings. The approach used is comprised of various phases, which are detailed in the subsections below.

2.1 Design of the Survey Questionnaire

The online survey questionnaire consisted of four main sections. The first section concentrated on assessing the effectiveness of the models and measures of materials procurement and the practices employed in procuring green materials in terms of C&DWR. The second section evaluated the effectiveness of Egyptian legislation regarding C&DWR. The third section evaluated the effectiveness of both awareness and cultural and behavioural aspects pertaining to the C&DWR. Essentially, the previous sections were administered to investigate the factors and elements influencing C&DWR concerning their efficacy in attaining the objectives of C&DWR. Finally, the fourth section assessed the level of agreement that could be achieved for the required and projected improvement for the various dimensions of projects (i.e. cost, time, and quality) employing C&DWR.

Close-ended questions using an ordinal scale were employed to make the questionnaire as straightforward as possible to complete. Based on studies by Vagias [40] and Brown [41], the five-point Likert scale was developed and utilised as an assessment tool to measure respondents' feedback for each question. A Likert scale was employed for assessing the effectiveness level of the different aforementioned factors that contribute to C&DWR as being elucidated in the literature studies and depicted in the theoretical framework, where "1" means "not effective at all" and "5" means "extremely effective". Moreover, an additional Likert scale was employed to assess the degree of agreement on the expected outcomes of C&DWR towards project dimensions' (i.e. time, cost, and quality) improvement, for which "1" means "strongly disagree" and "5" means "strongly agree".

2.2 Pilot Survey

Before gathering primary data, it was essential to establish the consistency of the anticipated responses and reliability of the chosen measurement method (i.e. the Likert scale) [42]. To that end, an initial pilot study was conducted to assess the survey's clarity, ease, comprehensiveness, and feasibility [39]. Saunders et al. [39] suggested a minimum sample size of ten individuals should be utilised for an

effective pilot survey. Consequently, 30 individuals participated in the pilot test; half were industry professionals and experts, while the remainder were academics with more than a decade of industry experience and teaching and research expertise. To test the reliability and consistency of the collected data, Cronbach's alpha was calculated for the range of the variables using SPSS V26[®] software. According to George and Mallery [43], the collected data from the pilot survey exceeded the threshold value of 0.70, indicating that reliability and consistency are maintained.

2.3 Sample Size–Targeted Participants

To calculate the sample size, three inputs were needed as follows: (1) population; (2) level of confidence; and (3) error margin (i.e. confidence interval). The representative sample size was determined from the population, estimated at 1,400 construction companies in Greater Cairo (GC). Conroy [44] claimed that the highest recommended confidence level in survey research is 95%, with a confidence interval ranging between 5 and 10%. As a result, this study selected a confidence level of 95%, with a confidence interval of 7.5%. Accordingly, the sample size of this study should not be less than 153 participants. Accordingly, the survey questionnaire was sent online to 360 participants with 244 responses, exceeding the required sample size.

3 Results and Discussion

The structural equation modelling (SEM) technique, utilising SmartPLS 3.3.2[®] software, was employed to analyse the collated data. SEM was adopted to test the theoretical framework, including the six hypotheses. The SEM is a general linear model technique for examining associations between IDVs and DVs. These variables can be observed directly as measured variables (i.e. indicators or items) or not as latent variables (i.e. constructs) [45, 46]. The primary goal of SEM is to explain and validate a proposed causal theoretical framework. The SEM is a validation procedure that relies on two steps as follows:

(1) The first step is validating the measurement model through confirmatory factor analysis (CFA) to test how well the measured indicators represent their relevant constructs.

(2) The second step is implementing the structural model and testing the research hypotheses through path analysis between the constructs.

Xiong et al. [47] claimed that SEM has been extensively used in social science and psychology research and has been replicated for use in construction research. Kline et al. [48] and Tenenhaus et al. [49] established that the partial

least squares (PLS) method of the SEM (PLS-SEM) is the most convenient for studies involving pragmatic settings. This is mainly due to its problem-oriented approach that aims to provide practical solutions for identified problems. A PLS-SEM analysis is an efficient alternative to ordinary least squares regression or covariance-based SEM (CB-SEM) for models, which includes IDVs and DVs. The PLS-SEM analysis can deal with multicollinearity among IDVs and generates IDVs based on cross-products and more robust predictions. It simultaneously tests the measurements and path models to produce more realistic assumptions [44, 45].

Accordingly, the PLS-SEM method is considered an efficient alternative to the CB-SEM. The PLS-SEM analysis was employed via SmartPLS 3.3.2[©] software because it offers the most widespread PLS-SEM method application [52]. The results of the PLS-SEM analysis and the evaluation tests of the theoretical framework are presented in the following subsections. Indeed, the PLS-SEM efficiently tests and validates the theoretical framework for various hypotheses. The refined integrated framework was developed and presented as a roadmap for improving the current situation in Egypt. On the other hand, the quantitative data of the online surveys were analysed statistically in the form of the mean and relative importance index (RII), whereby RII was used to rank the various factors influencing C&DWR in terms of their effectiveness. Sutanapong and Louangrath [53] asserted that using the mean and RII to explain, summarise, and visualise the gathered data in numerical and graphical representations highlights varied patterns arising from the data, which helps to convey meaningful information.

3.1 Assessment of Measurement Models

The measurement models, referred to as the outer models, describe the relationships between the constructs and their indicators (i.e. items). According to Hair et al. [54], measurement models could be reflective or formative, whereby reflective measurement models are widely used in social science research. The indicators of these models tend to reflect the effect of the underlying construct. This means that the causal effect is initiated from the construct to its indicators; therefore, as the same construct causes all of the indicators measuring it, there must be a high correlation between them. Moreover, all the indicators measuring a specific construct must be interchangeable so that if one of the indicators is removed, the reliability would still be acceptable, and ultimately the interpretation of the construct will remain unchanged [54]. Internal consistency, reliability, convergent validity, and discriminant validity must be evaluated when assessing reflective measurement models in PLS-SEM. Table 1 summarises the rules and

Table 1 Criteria of reflective measurement model assessment. Source: [47, 52, 55–58]

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

roadmap for evaluating the reflective measurement model. The structural model will be evaluated once the measurement model's reliability and validity have been established. The following subsections discuss the reliability and validity of the measurement model.

3.1.1 Internal Consistency Reliability

The internal consistency reliability examines whether all of the indicators associated with a construct are measured [59]. Hair et al. [58] claimed that it is recommended to utilise an additional internal consistency test, such as composite reliability, mainly because Cronbach's alpha has some limitations. For example, Cronbach's alpha does not give exact results for the reliability of random patterns, known as the upper bounds [60, 61]. Conversely, composite reliability assesses the internal consistency, considering each indicator has a distinct outer loading. Composite reliability overestimates the internal consistency reliability resulting in comparatively higher reliability estimates. It is generally explained in the same way as Cronbach's alpha, in which the composite reliability ranges between 0 and 1, and greater values indicate higher levels of reliability [58].

According to Hair et al. [58], composite reliability values that fall between 0.60 and 0.70 is sufficiently acceptable for exploratory research, whereas values ranging from 0.70 to 0.90 signify a high level of reliability and internal consistency for advanced stages of research (i.e. explanatory research). Accordingly, and in light of the aforementioned recommendations, the acceptable composite reliability value exceeding 0.70 was considered for this study. Therefore, this research has adopted a mixed approach of using Cronbach's alpha for measuring the lower bound, and the composite reliability for measuring the upper bound [58]. Therefore, the reliability was evaluated for each construct via the calculations provided by SmartPLS 3.3.2[©]. Table 2 demonstrates Cronbach's alpha and composite reliability values for all constructs. All

Table 2 Measurement model analysis' reliability

Construct	Cronbach's alpha	Composite reliability
GBPR	0.782	0.850
AW	0.875	0.923
LG	0.824	0.913
MPMO	0.818	0.916
CB	0.863	0.901
SLWC	0.937	0.955
LWPM	0.958	0.967
EMDM	0.942	0.958
WEBOQ	0.773	0.867
C&DWR	0.828	0.897

constructs have reliability values of more than 0.70, indicating that the constructs are highly reliable and have considerable internal consistency.

3.1.2 Convergent Validity

According to Hair et al. [62], convergent validity assesses the correlation between indicators assigned to measure the same construct. The outer loadings of the items and the

average variance extracted (AVE) are commonly used to assess the convergent validity of reflective measurement models. The recommended minimum significant outer loadings should not be less than 0.70 [54, 62]. AVE represents the grand mean of the squared loadings of the indicators measuring a construct. The AVE of a construct should be 0.50 or higher to be considered significant [62]. The AVE scores for all constructs in Fig. 2 were greater than 0.50. Conversely, Table 3 presents the AVE values of each construct, whereby Table 4 and Fig. 2 indicate the outer loadings for each construct. The values of outer loadings were found to be more than the 0.7 threshold value for all reflective measuring models, indicating that the reliability of the indicators is high.

3.1.3 Discriminant Validity

Henseler et al. [57] recommended that the discriminant validity be assessed using the Hetrotrait-Monotrait (HTMT) ratio after establishing the convergent validity. The discriminant validity of a construct is determined by its difference from other constructs. HTMT is defined as 'the ratio of the between-trait correlations to the within-traits correlations' [48]. Specifically, it is the average of the correlations of indicators across constructs measuring

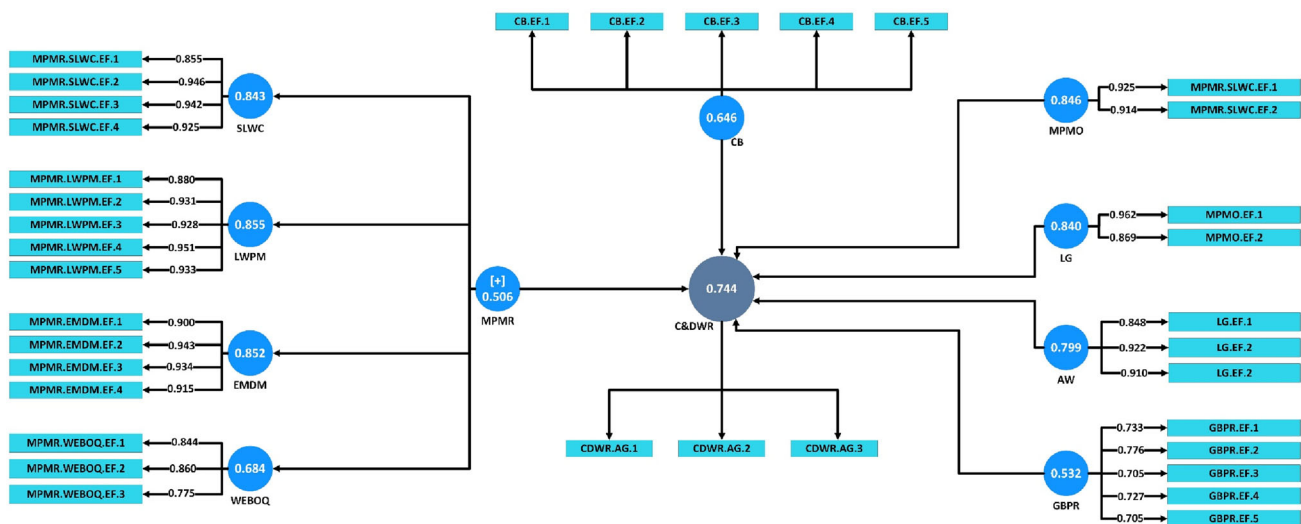


Fig. 2 Outer loadings and AVE for different constructs in the research model

Table 3 Average variance extracted (AVE) of different constructs

Construct	GBPR	AW	LG	MPMO	CB	MPMR
AVE	0.532	0.799	0.84	0.846	0.646	0.506
Construct	SLWC	LWPM	EMDM	WEBOQ	C&DWR	
AVE	0.843	0.855	0.852	0.684	0.744	

Table 4 Item loadings of different constructs

	Items	GBPR	AW	LG	MPMO	CB	SLWC	LWPM	EMDM	WEBOQ	C&DWR
GBPR	GBPR.1	0.733									
	GBPR.2	0.776									
	GBPR.3	0.705									
	GBPR.4	0.727									
	GBPR.5	0.705									
AW	AW.1		0.848								
	AW.2		0.922								
	AW.3		0.91								
LG	LG.1			0.962							
	LG.2			0.869							
MPMO	MPMO.1				0.925						
	MPMO.2				0.914						
CB	CB.1					0.795					
	CB.2					0.827					
	CB.3					0.865					
	CB.4					0.77					
	CB.5					0.758					
SLWC	SLWC.1						0.855				
	SLWC.2						0.946				
	SLWC.3						0.942				
	SLWC.4						0.925				
LWPM	LWPM.1							0.88			
	LWPM.2							0.931			
	LWPM.3							0.928			
	LWPM.4							0.951			
	LWPM.5							0.933			
EMDM	EMDM.1								0.9		
	EMDM.2								0.943		
	EMDM.3								0.934		
	EMDM.4								0.915		
WEBOQ	WEBOQ.1									0.844	
	WEBOQ.2									0.86	
	WEBOQ.3									0.775	
C&DWR	C&DWR.1										0.834
	C&DWR.2										0.881
	C&DWR.3										0.872

different phenomena relative to the average of the correlations of indicators within the same construct [57]. If the model constructs are conceptually similar, the value of HTMT should be below 0.90. In contrast, the model constructs are conceptually distinct when the value of HTMT is less than 0.85. The HTMT values for all constructs were computed and found below the predefined threshold of 0.85. The HTMT values for the constructs are indicated in Table 5, and it was found that the HTMT values of all

constructs were less than 0.85. This suggests that discriminant validity is accomplished for all the constructs.

3.2 Assessment of Structural Model

The structural model, also called the inner model, depicts the relationship connecting the factors [62, 63]. The structural model has been developed based on an extensive literature review, whereby the order of the constructs must be based on theory, logic, or observations [57]. The

Table 5 HTMT values

	AW	CB	C&DWR	EMDM	GBPR	LG	LWPM	MPMO	SLWC	WEBOQ
AW										
CB	0.529									
C&DWR	0.661	0.664								
EMDM	0.334	0.174	0.271							
GBPR	0.631	0.457	0.624	0.185						
LG	0.014	0.089	0.119	0.056	0.124					
LWPM	0.664	0.428	0.615	0.284	0.539	0.055				
MPMO	0.563	0.762	0.65	0.186	0.413	0.036	0.421			
SLWC	0.349	0.287	0.365	0.63	0.26	0.054	0.493	0.307		
WEBOQ	0.509	0.465	0.469	0.654	0.357	0.026	0.564	0.309	0.735	

Table 6 Criteria for assessing the structural model. Source [50, 53, 55, 57, 59, 64, 69, 70]

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 (R^2)	$R^2 < 0.19$, unacceptable predictive accuracy; $R^2 = 0.19 - 0.33$, small predictive accuracy; $R^2 = 0.33 - 0.67$, moderate predictive accuracy; $R^2 \geq 0.67$, high predictive accuracy
Effect size (f^2)	$f^2 < 0.02$, no effect; $f^2 = 0.02 - 0.15$, small effect; $f^2 = 0.15 - 0.35$, moderate effect; $f^2 \geq 0.35$, high effect
Cross-validated redundancy (Q^2)	Predictive relevance using blindfolding; $Q^2 > 0$
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

relationships within the structural model of this study are considered cause-and-effect relationships. Causal links or relationships are direct relationships between the factors in which one factor predicts the other. The structural model for this study was specified in the theoretical framework. The model consists of first-order constructs except for one construct (i.e. MPMR), which is a second-order construct. The first-order constructs have observed variables (i.e. items) as construct indicators. On the other hand, second-order constructs have other unobserved constructs as their indicators, while these unobserved constructs have observed variables (i.e. indicators). First-order constructs are measured at one level of abstraction, while second-order constructs are measured at two levels of abstraction [58].

After establishing the reliability and validity of the measurement models, the structural model should be assessed. The structural model's evaluation comprises assessing the model's predictive power and relationships between the constructs and assessing the relationships between the constructs in the model [56, 64, 65]. 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). Table 6 summarises the utilised criteria in this study to evaluate the structural model. According to review studies [51, 62, 66–69] of the PLS-SEM, researchers often report these criteria during the analysis of the structural model. The criteria and guidelines in Table 7 below indicate these assessments' outcomes in the following sub-sections.

3.2.1 Multicollinearity

Hair et al. [58] established that collinearity happens when there is a strong correlation between two constructs, which results in interpretation and assessment challenges. When more than two constructs are included in collinearity, multicollinearity arises. The variance inflation factor (VIF) is often used to analyse multicollinearity. It is derived by dividing “one” by “tolerance”, which refers to the variance explained by one independent construct that is not explained by the other independent constructs [58, 63]. A

Table 7 Variance inflation factors for IDVs

Independent variables	AW	CB	GBPR	LG	MPMO	MPMR
VIF	1.861	1.945	1.465	1.024	1.888	1.448

Table 8 Model path coefficients

Path	β	Standard deviation	t value	P value
AW→ C&DWR	0.188	0.059	3.192	0.001***
CB→ C&DWR	0.217	0.073	2.963	0.003**
GBPR→ C&DWR	0.231	0.057	4.069	0.000***
LG→ C&DWR	0.106	0.052	2.037	0.042*
MPMO→ C&DWR	0.174	0.074	2.357	0.019*
MPMR→ C&DWR	0.152	0.055	2.754	0.006**
MPMR→ EMDM	0.751	0.033	23.112	0.000***
MPMR→ LWPM	0.741	0.045	16.326	0.000***
MPMR→ SLWC	0.863	0.023	38.288	0.000***
MPMR→ WEBOQ	0.82	0.027	30.407	0.000***

* $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$

high multicollinearity problem occurs when **VIF** is equal to or higher than 5, with a tolerance value of 0.20 or lower [56, 63]. Table 7 demonstrates all the **VIF** values for the data analyses found to be less than the cut-off threshold, indicating no multicollinearity between the independent constructs.

3.2.2 Path Coefficients

The estimations of the relationships between the model’s constructs are referred to as path coefficients [62]. The coefficients range from + 1 to –1, with + 1 indicating a substantial positive correlation, 0 indicating a negligible or non-existent correlation, and –1 indicating a substantial negative correlation [52]. In addition to the

significance level (α), ***t* value**, and ***P* value**; path coefficients (β) should also be reported when evaluating PLS paths [67]. Ringle et al. [66] examined the studies published for the tenure between 1992 and 2011 in ‘Management Information Systems (MIS) Quarterly’ that employed the PLS-SEM, and they found that the vast majority of these studies provided path coefficients (β), significance level (α), ***t* value**, and ***P* value** upon investigating the structural model. Chin [70] stated that evaluating the model’s quality should also be based on the path coefficients’ direction and significance levels. Therefore, these values are represented for the path analysis test. Accordingly, this study adopted a significance level (α) of 5%, in which the *P* value should be less than 0.05 and the *t* value should be greater than 1.96 to evaluate the relationship as statistically significant [58]. However, if *P* value is less than 0.05 and *t* value is greater than 1.96, thus it suggests that there is enough evidence to refute the null hypothesis H_0 (i.e. the IDV has no effect on the DV) in favour of the alternative hypothesis H_1 (i.e. there is a positive effect of the IDV on the DV). Table 8 as well as Fig. 3 show the model β -values interconnected with its *t* values and *P* values.

Notably, “AW” demonstrates a statistically significant positive impact on C&DWR; since $\beta = 0.188$, $t = 3.192$, and $P \leq 0.001$. CB” has a significant positive statistical impact on C&DWR; since $\beta = 0.217$, $t = 2.963$, and $P < 0.01$, whilst “GBPR” has a statistically significant positive impact on C&DWR; since $\beta = 0.231$, $t = 4.069$, and $P < 0.001$. “MPMO” has a significant positive statistical impact on C&DWR; since $\beta = 0.174$, $t = 2.357$, and $P < 0.05$ and “MPMR” has a statistically significant positive impact on C&DWR; since $\beta = 0.152$, $t = 2.754$, and $P < 0.01$. Finally, “LG” has a statistically significant positive

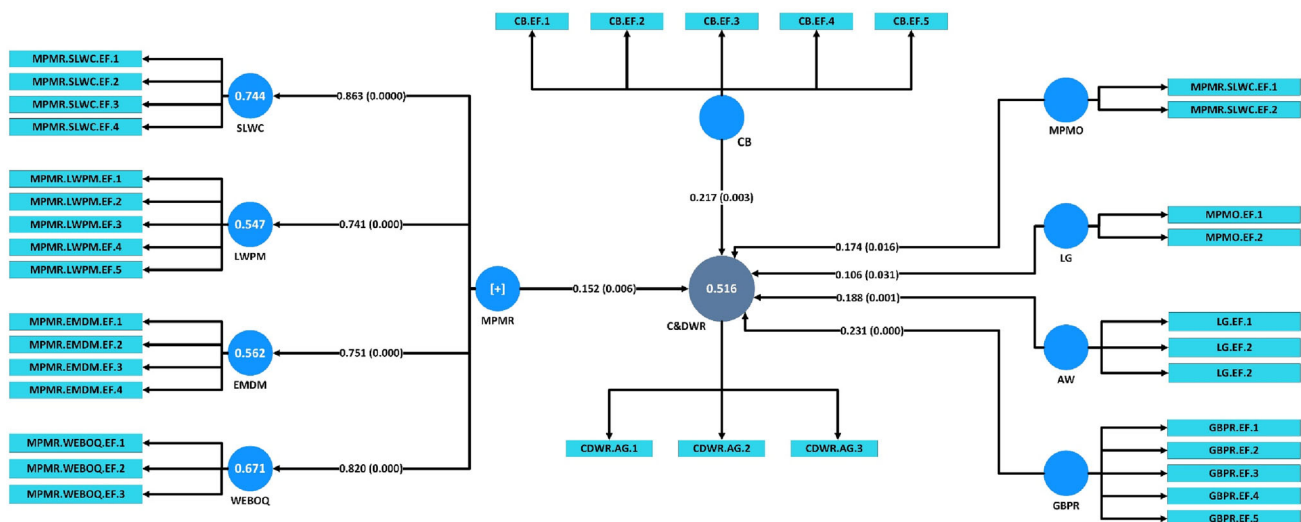


Fig. 3 Path coefficients with corresponding *P* values and R^2 adj value of DV

impact on C&DWR; since $\beta = 0.106$, $t = 2.037$, and $P < 0.05$. These results indicate robust and sufficient evidence to refute the null hypotheses in favour of all the proposed hypotheses in this study.

3.2.3 Coefficient of Determination (R^2)

Coefficient of determination (R^2) relates to the influence of IDVs on the DV [67], which is one of the structural model's quality measures [62]. Hair et al. [67] have examined 204 research papers that utilised the PLS-SEM and discovered that R^2 is the primary structural model evaluation criterion. Similarly, Ringle et al. [66] examined plethora of research that employed the PLS-SEM in information systems and discovered that R^2 was reported in 105 of 109 models. R^2 values vary from 0 to 1, whereby, 0 indicating low explained variance and 1 indicating high explained variance. Strikingly, the value of R^2 is controversial, whereas, in marketing research, Hair et al. [56] claimed that, R^2 values of 0.25, 0.50, or 0.75 are low, moderate, and high, respectively. However, in business research, Chin [70] argued that R^2 with a value of 0.19, 0.33, or 0.67 are low, moderate, and high, respectively.

According to Hair et al. [58] and Henseler et al. [71], researchers should report the adjusted R^2 (i.e. R^2_{adj}) values that consider the IDVs' number and sample size. Adding more IDVs leads to an increase in R^2 values; however, the R^2_{adj} compensates for this by taking complexity of the model into consideration [58]. Furthermore, the R^2_{adj} values are essential to assessing the quality of various models or comparing the model across different contexts [71]. The results of R^2_{adj} are reported in Table 9 and demonstrated in Fig. 3. The R^2 value of the model is equal to 0.528 and its R^2_{adj} value is equal to 0.516, which indicates that about 52% of the variations in C&DWR are explained by the variations in the IDVs.

3.2.4 Effect Size (f^2)

The effect size (f^2) is a measure of how much the endogenous construct will be affected if an exogenous construct (i.e. IDV) is removed from the model, leading to a change in R^2 value of the model [58]. The f^2 values are computed using the SmartPLS[®] software. A construct is

considered to have a small effect if its f^2 value is between 0.02 and 0.15, whilst it is considered to have a medium effect if its value is between 0.15 and 0.35, and a large effect if its value is greater than 0.35 [58]. According to Hair et al. [54], a construct with f^2 value < 0.02 means it has no effect on the endogenous construct. Table 10 presents the f^2 effect size of the constructs.

The results show that all the IDVs' have small effects on the DV. Despite that, the removal of any IDV will affect the DV leading to a drastic change in R^2 value of the model. The "GBPR" has the largest effect size among the IDVs, and "LG" has the smallest effect size among the IDVs. The IDVs can be ranked from highest to lowest according to their effect size as follows: (1) GBPR; (2) CB; (3) AW; (4) MPMR & MPMO; and (5) LG.

3.2.5 Predictive Relevance (Q^2)

Predictive relevance (Q^2) value represents the out-of-sample predictive power of the model [58]. When a model is considered to have predictive power or predictive relevance, it may anticipate data that was not deployed in the model estimation accurately. The Q^2 value is calculated through running a blindfolding procedure. An omission Distance (D) must be specified prior to running this procedure. Hair et al. [58] suggested specifying a D between 5 and 12 while carefully considering the fact that the sample size divided by the selected D will not generate an integer. The omission distance indicates that while running the blindfolding procedure, every d^{th} data point of the endogenous construct's items will be omitted and then predicted. 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. The number of blindfolding rounds always equals omission distance D .

The omitted data points are considered missing values and treated accordingly using pairwise deletion or mean value replacement when running the PLS-SEM. The resulting estimates are then used to predict the omitted data points. The difference between the true (i.e. the omitted) data points and the predicted ones is then used as the input for calculating the value of Q^2 . An endogenous construct's

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

	R^2	R^2_{adj}	Predictive accuracy
C&DWR	0.528	0.516	Moderate

Table 10 The effect size of IDVs

	AW	CB	GBPR	LG	MPMO	MPMR
Effect size	0.04	0.051	0.077	0.023	0.034	0.034
Evaluation	Small	Small	Small	Small	Small	Small

Table 11 Predictive relevance

	SSO	SSE	$Q^2 (= 1-SSE/SSO)$
C&DWR	720	469.633	0.348

Q^2 value greater than 0 indicates the model's predictive relevance for this construct [54]. Based on the recommendation of Hair et al. [51], an omission distance D of 10 was selected to examine the predictive power of the model, in which the sample size (i.e. 244) divided by the selected D (i.e. 10) did not produce an integer. Table 11 presents the Q^2 values of the analysis and the value of Q^2 for C&DWR in Table 11 is greater than 0; thus, it is unequivocally concluded that the model has a decent predictive relevance.

3.2.6 Goodness of Fit of the Model

Tenenhaus et al. [49] proposed the goodness of fit (GoF) as a global fit indicator. GoF is the geometric mean of both the average of AVE values and R^2 values of the endogenous variables. The AVE values are previously listed in Table 4. The values of R^2 are listed in Table 12.

GoF aims to consider the research model at both levels (i.e. the measurement and structural models), emphasising the overall model performance [64]. The GoF index can be calculated using Eq. 1, as follows:

$$\text{GoF} = \sqrt{R^2 \times \text{AVE}} = \sqrt{0.612 \times 0.741} = 0.673. \quad (1)$$

Table 6 lists the GoF criteria for determining whether GoF values are unacceptable, minor, moderate, or high enough to be considered a globally adequate PLS model. According to these criteria and given the GoF index calculated value, it is concluded that the model's GoF is large enough to be deemed adequately valid as a global PLS model.

3.3 Analysis of Importance–Performance Map

The importance–performance map analysis (IPMA) is used for identifying predecessors (i.e. IDVs), which have relatively high importance (i.e. strong total effect) for the targeted construct (i.e. DV) but also relatively low

Table 12 Values of R^2 for different constructs in the model

Construct	SLWC	LWPM	EMDM	WEBOQ	C&DWR
R^2	0.745	0.549	0.564	0.673	0.528

performance (i.e. low average latent variable scores) [58]. These constructs having such characteristics represent potential areas of improvement that should receive greater attention to improve the DV. These scores' mean values indicate the construct's performance, with 0 representing the lowest and 100 representing the highest performance, as shown in Table 13. It can be concluded that the “CB” construct is the second most crucial factor contributing to C&DWR; however, it has the lowest performance among the six contributing factors. Accordingly, there is substantial room for improvement for the “CB” in the Egyptian construction industry to achieve the aspired results towards C&DWR. These results warrant prompt and strict actions to be taken to improve the culture and behaviour toward C&DWR in the construction sector in Egypt.

3.4 Effectiveness of Different Factors Affecting C&DWR

The effectiveness of the factors was ranked using the RII formula, in which RII is calculated using Eq. 2 as early investigated by Olomolaiye et al. [72] and Shash [73].

$$\text{RII} = \frac{\sum W}{AN}, \quad (2)$$

where “W” denotes the weights assigned to each item depending on its level of effectiveness. It is scaled from 1 to 5, where 1 indicates it is not effective at all, and 5 indicates it is extremely effective. On the other hand, “A” indicates the greatest weight on a rating scale (i.e. 5 in this study), and “N” denotes the total number of respondents [74]. The RII value ranges from 0 to 1, where higher RII values indicate a more effective factor than other factors with lower RII scores. As a result, the factors in each category are ranked based on their RII values, as shown in the next section and investigated in detail by Daoud et al. [31]. The analysed results entail developing a roadmap to assist the policymakers and the construction industry professionals in reducing C&DW in Egypt.

Table 13 Importance–performance matrix of IDVs

IDV	Importance	Performance
AW	0.212	89.033
CB	0.238	72.080
GBPR	0.293	92.169
LG	0.096	78.400
MPMO	0.143	75.718
MPMR	0.181	83.236

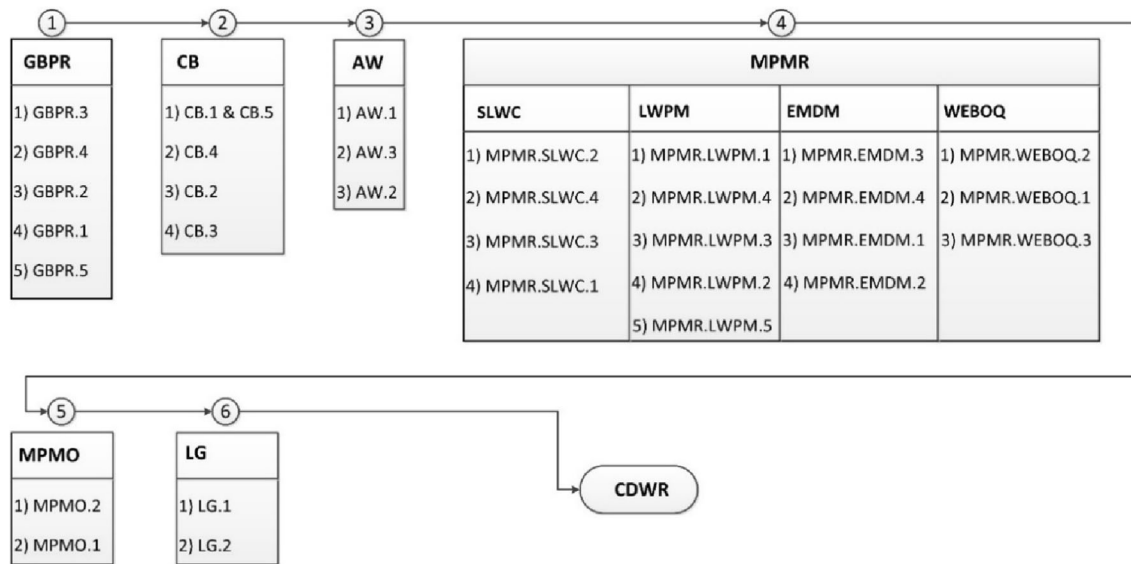


Fig. 4 Roadmap for implementing the integrated framework

4 Roadmap for Implementing the Integrated Framework in the Egyptian Construction Industry

Based on the results of effect size analysis and the importance–performance matrix of the IDVs, and the results of RII analysis for the effectiveness of different IDVs components (i.e. items) the following roadmap is introduced to set and prioritise the application of the different factors along with their various components and measures in a sequential manner. The authors strongly recommend that the policymakers and construction professionals strictly adhere to the proposed roadmap, which undoubtedly will contribute to reducing C&DW in the construction industry in Egypt. This roadmap arranges the application of the different factors in descending order based on their weightings (i.e. effect size and importance) and the application of their measures and components based on their level of importance resulting from RII analysis of their effectiveness. The different IDVs were arranged in descending order according to their weightings. The roadmap for implementing the integrated framework is summarised in Fig. 4. As illustrated in Fig. 4, the six factors' components are listed in descending order based on their RII analysis.

5 Conclusion

Although the construction industry strives to adopt innovative management strategies, it continues to suffer from repercussions of the C&DW within the global construction industry. This study established that C&DW in Egypt is a critical issue for the government and the construction sector, whereby C&DW accounts for up to 40% of the overall materials costs in construction projects. Surprisingly, indiscriminate dumping is the predominant way of dealing with C&DW in Egypt, severely affecting the environment and society. This study proposed an insightful approach through evaluating the influence of six main factors for C&DWR in Egypt, in addition to developing a novel integrated framework to assist the policymakers and construction industry professionals in reducing C&DW in light of Egypt's vision 2030. The study revealed that "GBPR" has the highest effect on the C&DW in Egypt, while "LG", "MPMO", and "MPMR" have the least effect, respectively. Moreover, reducing the C&DW in Egypt is intrinsically linked with the low performance of the "CB". Accordingly, "CB" entails immediate actions to achieve the desired outcomes for C&DWR. Unequivocally, the developed roadmap paves the way for the decision makers to follow easy steps to implement the proposed integrated framework. The proposed roadmap will highly assist the government and the construction industry in reducing C&DW in Egypt significantly.

Data availability The data that support the findings of this study are available on request from the corresponding author.

Declarations

Conflict of Interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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