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Investigating Barriers to the Adoption of Energy Management Practices for Sustainable Construction Projects: SEM and ANN Approaches

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Abstract

This research addresses the critical challenges hindering the integration of Energy Management Practices (EMPs) within the construction industry, impeding its progress toward sustainability. Recognizing the pivotal role of EMPs in fostering sustainable practices, this study aims to fill a notable research gap by conducting a meticulous survey involving 100 industry professionals. Through the application of Partial Least Squares Structural Equation Modeling (PLS-SEM) and Artificial Neural Network (ANN) analyses, this study provides a comprehensive exploration of the intricate barriers and their interrelated dynamics within the construction sector. The findings reveal significant financial obstacles, including higher initial costs and limited financing options, underscoring the need for interventions to alleviate financial constraints. Additionally, policy and regulatory challenges, such as limited government incentives and shifting energy management rules, are identified, highlighting the necessity for stable and supportive regulatory environments to foster EMP adoptions. This research provides unique insights into the barriers hindering EMP adoption within the construction sector. The implications of this study extend beyond EMP adoption, offering a foundation for advancing sustainable practices in the construction industry. The insights gained can inform both academic research and practical decision-making, contributing to the ongoing discourse on sustainability in construction.

Keywords: Barriers; Energy Management Practices (EMP); Construction Industry; Overall Sustainable Success (OSS); Partial Least Squares Structural Equation Modeling (PLS-SEM); Artificial Neural Network (ANN).

1. Introduction

Stricter energy, environmental regulations, and sustainable infrastructure are needed to balance the environment, the economy, and society. For example, the International Energy Agency (2018) states that 36 percent of global energy consumption and 40 percent of carbon dioxide emissions are directly attributable to the building sector. Every construction project is different due to its complexity (such as project size, duration, and intricacy). Thus, these unique characteristics present new and unique obstacles for construction specialists to overcome, even with the application of cutting-edge technology [1, 2]. Identifying the barriers preventing the local construction industry from understanding and implementing energy-efficient solutions [3]. It is thought that the employment of cutting-edge technology to encourage energy conservation in various construction projects is severely limited by the absence of financial support, loans, and subsidies from financial institutions [4]. On the other hand, government incentives such as lower consumer energy bills may convince financiers to back profitable building projects (United Nations Industrial Development Organization).

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The rate and instances of successful energy management adoption in building projects can also be increased by government energy conservation policies, such as taxation, and financial support from financial institutions, such as loans and subsidies for energy conservation initiatives [5, 6]. Every phase of a construction project requires energy, and different natural resources are required from the beginning of work until the buildings are destroyed. Resources are required for raw material extraction, manufacture, usage, and transportation, which is the leading cause of this [7, 8]. Energy-intensive building projects require a significant amount of energy upfront. Furthermore, valuable environmental resources are also used when a structure is being demolished. These operations often generate large volumes of solid trash. As defined by Kangas et al. [9], life cycle energy is the total energy needed by a structure from the time of construction to its demolition. It is crucial to make this distinction.

Two forms of energy are used in buildings: operating energy and embedded energy [10–12]. The quantity of energy required to produce, prepare, manufacture, and deliver building supplies to the construction site is known as embodied energy. Manufacturing equipment and building materials requires fully exploiting resources [13]. Raw materials must be extracted, processed, and transported using embodied energy. Following that, this energy is used for building construction, transit, retrofitting, and, in the end, building demolition [14, 15]. Conversely, operating energy usually refers to the energy required to run machinery, utilize water, and maintain the interior environment of the structure [16]. The installed electrical appliances in our homes are often controlled by the HVAC system, which commonly uses operating energy [17].

Two primary energy sources are typically utilized in construction. One of these is electricity, and the other is fossil fuel. Similar to gasoline and diesel, the primary use of fossil fuels is in the production of automobiles and heavy machinery. Most construction projects require fuels like diesel, although certain projects usually use electricity. The specifics of the building project will determine the kind of energy source to be used; modifications could be made [18]. Diesel fuel is the primary energy source utilized in construction operations globally, accounting for 70–80% of the required and desired energy. The remaining twenty to twenty-five percent comes from electricity. Heavy machinery like loaders, diggers, dumpers, and mobile cranes needs much energy [19]. Nonetheless, just 5.968 million gallons of diesel, or 1.2% of all energy used in the country, are utilized for heavy construction machines each year in the United States (U.S. Environmental Protection Agency).

A contractor oversees the processes, equipment usage guidelines, and other duties prior to the start of the major construction project [20, 21]. Embodied energy is used at every stage of the project life cycle, from start to finish, and particularly from the contractor's perspective. A few of the numerous duties needed include purchasing the raw materials for the input, transporting necessary project resources (such as heavy equipment, building supplies, trucks, and operators), and building construction (including foundation, assembly, painting, and designing) [22]. Darko et al. [23] define energy management as calculating and monitoring a building's energy usage and efficiently and economically conserving energy. According to Fernando & Hor [24], energy management is the economical, environmentally conscious, and economical use of energy to maximize profit. Energy efficiency maximizes production while using the least energy resources possible [25]. Thus, the implementation of energy management programs (EMPs) is aided by energy monitoring systems, energy conservation, the appropriate use of energy-efficient equipment, and the identification of possible energy savings [26]. Notably, industrialized countries and the global community are closely monitoring electromagnetic pulses (EMPs) and trying to use them in energy-efficient construction projects. However, developing countries continue to depend on traditional energy sources.

The utilization of petroleum, diesel, and gasoline remains prevalent, particularly in countries such as Saudi Arabia, where societal responsibilities towards environmental preservation and natural resource conservation are often disregarded. This situation is exacerbated by low literacy rates, widespread ignorance, and a general reluctance to embrace innovative, eco-friendly technologies. Consequently, several driving forces underpin the adoption of Energy Management Practices (EMPs), including the implementation of new national regulations emphasizing energy efficiency in building projects, the rising costs associated with conventional energy sources, and efforts aimed at enhancing the efficiency of the construction process [27]. Various initiatives, such as the Energy Efficiency Management Project (EEMP), Energy Efficiency and Capacity (EEC), Energy Standards & Labelling Scheme (ESLS), and Energy Conservation Building Codes, have been established to promote EMPs. However, despite these initiatives, the construction sector has been slow to adopt EMPs due to numerous challenges. One significant issue is the lack of attention paid to EMPs in construction projects, particularly in developing countries like Saudi Arabia [28].

To fill this gap, this study aims to comprehensively investigate the barriers to EMP adoption within the construction industry. It employs a dual-method approach, utilizing Structural Equation Modeling (SEM) and Artificial Neural Network (ANN) analyses. The primary objectives include conducting an extensive literature review to identify gaps, quantifying and prioritizing barriers through a targeted survey of professionals engaged in Saudi Arabian construction maintenance projects, and utilizing SEM to unravel the interrelationships among these barriers. Additionally, the study aims to explore nonlinear dynamics using the ANN approach. The contribution of this research lies in providing a holistic understanding of the barriers to EMP adoption, offering quantitative insights through advanced analytics, furnishing actionable recommendations for stakeholders, advancing methodological approaches, and ensuring contextual relevance by focusing on the specific nuances of the Saudi Arabian construction sector. Ultimately, this study aims to pave the way for strategic interventions that enhance EMP adoption and contribute to the sustainable success of construction projects.

2. Literature Review

2.1. EMPs and the Global Construction Sector

Using renewable energy in building projects has become a significant worldwide concern. The idea of using EMPs in building projects has come to light to address the serious issues surrounding the use of renewable energy sources. Numerous nations are addressing the problems of energy management and carbon emissions globally. Persson & Grönkvist [29] note that in this regard, Latin America developed strategic strategies for the application of electromagnetic pulses (EMPs) in residential and commercial building projects. Scholars from several nations have also developed original frameworks and models to assist energy-saving initiatives during the building process. Most prior international research has concentrated on aspects of EMPs, such as energy consumption [30], carbon reduction (Gopinath et al. 2020), and project cost minimization [31]. According to Zhang et al. [32], energy management and utilization frequently significantly impact how construction projects can evolve sustainably. When construction organizations make management decisions, energy management during the building process typically gets less attention [33–35]. The primary reasons are the clients' lack of interest and the government's lack of incentives. However, outside pressure from clients and other stakeholders about using EMPs has compelled the construction industry in several industrialized nations to adopt new sustainable practices [36]. Furthermore, contracting organizations' perspectives have shifted from traditional energy consumption ways to sustainable energy practices due to the strict rules in European nations targeted at putting EMPs into place [37]. According to Hesselink & Chappin [38], environmental protection awareness programs assist the construction industry in efficiently managing energy usage, potentially improving the status of the participating firms.

2.2. Barriers to Adopting EMPs

The various obstacles that prevent the use of EMPs in construction operations have been the subject of numerous studies. According to Liu et al. [39], the length and cost of a construction project are connected criteria, and both are necessary for a precise evaluation of the project's effectiveness and completion [40]. According to Davies et al. [41], project cost is one of the biggest obstacles to incorporating sustainable practices in building projects. Regarding this, Gupta et al. [42] discovered that a significant obstacle to adopting sustainable construction is the Chinese government's and important legislative agencies' poor policy execution. Furthermore, Moglia et al. [43] identified specific barriers to green building, especially in Asia. These include staff members' poor self-esteem regarding their ability to persuade customers to adopt sustainability, a lack of knowledge about sustainable technologies, and inadequate training or education for energy management and green building. Furthermore, Caputo & Pasetti [44] found that a lack of client demand is one of the biggest obstacles to implementing sustainable construction projects.

According to Azizi et al. [45], the lack of sustainable building regulations for labeling and registration is another obstacle inhibiting the use of green construction techniques. Furthermore, Li et al. [46] identified a number of difficulties that emerge from developing new business models that are mainly in favor of sustainability and the green transition, particularly in Northern Europe. They also provided a scientific solution to the issues that sustainable business models in the building industry, which is part of the industrial sector, encounter. A few of the issues mentioned are decreased customer demand, scarce investment resources, opposition to implementing sustainable practices, insufficient regulation, a lack of government participation, and a lack of knowledge about energy efficiency. Organizational impediments include mistrust between contractors and developers, a divide in stakeholder communication and knowledge sharing, a lack of coordination between management and staff, and a lack of enthusiasm for the research and development projects that organizations undertake [47].

According to Trinh et al. [48], financial restraints are one of the biggest obstacles to using green energy in building projects. These include increased expenses, a lack of government assistance, and a dearth of funding and financial institution subsidies. Furthermore, Żuk [49] discovered several essential factors seriously impede the building industry's ability to apply energy-saving measures. These include the absence of government and financial institution support, the general public's ignorance of sustainable building methods, the dearth of stakeholder conferences and training sessions, and the top leadership's indifference. Moreover, several barriers prevent the adoption of innovative and energy-saving solutions [50]. These include the knowledge gaps between clients and contractors, a lack of funding, and a lack of professional competency. Furthermore, inadequate governmental policies and directives significantly impede the successful and efficient adoption of eco-friendly technologies [51]. Despite these obstacles, bringing cutting-edge technology and ensuring they are integrated into construction projects related to energy management can give investors a competitive edge in the market [52].

From a business standpoint, a few adjustments are needed to overcome the obstacles to greater energy efficiency. Ikudayisi et al. [53] enumerate several of these obstacles, the most prevalent being ignorance, a lack of investment opportunities, energy expenses, decision-making processes, and the requirement for expensive, precise information. In addition, there are some obstacles that project contractors need to surmount to hinder the implementation of sustainable building practices in poor nations. According to Tafesse et al. [54], these problems include unethical government engagement, a lack of trained personnel, a lack of technology, and a lack of possibilities for employee training. Numerous prior studies conducted globally have impeded the adoption of green construction methodologies. Employees [55], consumers and market obstacles [54], stakeholder affiliation, awareness, and attitudes [53], and a lack of policies and procedures [44, 43] have identified numerous underlying explanations for the limited adoption of green construction. Gupta et al. [42] found that the cost of green construction techniques is a significant barrier to deployment. The study investigated the application of sustainable practices in Chinese building projects.

Funding for innovative sustainable technology is also seen as a financial obstacle when considering the client's purchasing power [41, 47, 48]. Various preferences or a lack of readiness to embrace change may prevent customers from choosing energy-efficient solutions [46]. Furthermore, social influence often leads people to adopt the superstitious beliefs of their peers. This makes it challenging for people to adapt to change effectively and efficiently, including utilizing energy-saving technologies in building projects [45]. Within this framework, Pietrosemoli & Rodríguez Monroy [36] noted barriers to energy management implementation in Italian building projects. The primary problems found were a lack of understanding of energy management concerns, challenges in establishing municipal objectives, the difficulty of gathering and analyzing data, and a shortage of experts in businesses to collect and evaluate data and create effective strategies. Fu et al. [35] state that relevant stakeholders adopt EMPs progressively. The progress of environmentally conscious buildings mainly depends on the availability of knowledge and information since modern green technologies are more sophisticated than those found in conventional buildings.

There are several significant challenges to be aware of when pursuing brownfield rehabilitation, controlling the initial cost of construction projects, and incorporating sustainability. These include financial institutions and quasi-governmental organizations that support government incentives and subsidies, high taxes, cash availability restrictions, energy conservation, and environmental deterioration [34]. According to Umar et al. [40], a significant obstacle to adopting energy-efficient construction practices is a lack of knowledge and awareness. According to Martek et al. [33], the ultimate goal of the stakeholders may be impacted by the top management's insensitivity and ignorance regarding adopting green techniques in building projects. Moreover, according to Liu et al. [39], a lack of cooperation and communication among stakeholders hinders the application of green practices in the building sector. The reluctance of clients to make demands is one of the main obstacles to the Saudi Arabia construction industry's adoption of energy conservation [38].

2.3. Overall Sustainable Success

Sustainable success in the construction industry encompasses a multifaceted approach, considering social, economic, and environmental dimensions. Achieving a harmonious balance between these elements is imperative for the long-term viability and positive impact of construction projects.

2.3.1. Social Sustainability

Social sustainability involves addressing the human aspects associated with construction projects. In the context of the discussed challenges, it becomes crucial to focus on education, awareness, and community engagement [27]. The text highlights that in certain regions, such as Saudi Arabia, low literacy rates and a lack of awareness contribute to the reliance on traditional energy sources. To promote social sustainability, initiatives should be undertaken to increase literacy rates, raise awareness about environmental responsibilities, and foster a willingness to embrace innovative, eco-friendly technologies. By incorporating social considerations, construction projects can become catalysts for positive societal change.

2.3.2. Economic Sustainability

Economic sustainability is central to the overall success of construction projects [4]. The text emphasizes the limitations posed by the absence of financial support, loans, and subsidies for energy-efficient solutions. To address this, financial institutions need to play a proactive role in supporting construction projects that prioritize energy efficiency [4]. Government incentives, such as tax benefits and financial support, can further encourage financiers to invest in economically viable and environmentally conscious building projects [5, 6]. Economic sustainability ensures that construction initiatives not only meet current financial needs but also contribute to long-term economic growth and stability.

2.3.3. Environmental Sustainability

The environmental dimension is a key focus in the pursuit of overall sustainability [1]. The text underscores the significant impact of the construction sector on global energy consumption and carbon dioxide emissions. Stricter energy and environmental regulations, along with sustainable infrastructure, are essential components of environmental sustainability [1]. Energy management programs (EMPs) and the adoption of electromagnetic pulses (EMPs) are identified as potential strategies to enhance energy efficiency in construction projects [26]. The life cycle approach, considering embodied energy and operating energy, emphasizes the importance of minimizing environmental impacts from the extraction of raw materials to the demolition of buildings [14, 15]. Overall, achieving overall sustainable success in construction requires a holistic approach that addresses social, economic, and environmental dimensions [27]. By promoting social awareness, securing economic support, and implementing environmentally conscious practices, the construction industry can contribute positively to communities, economies, and the global environment.

2.4. Research Gaps

While prior research has delved into barriers to the adoption of EMPs in the construction industry, there exists a notable research gap concerning the holistic investigation of these barriers and their implications for the overall sustainable success of construction projects. Many studies have focused on individual aspects or specific barriers, often lacking a comprehensive approach that integrates various dimensions and their collective impact on project sustainability. Additionally, the use of advanced analytical methods, such as SEM and ANN, to understand the intricate relationships among identified barriers and their influence on sustainable outcomes is an underexplored area. The existing literature primarily lacks a robust and integrated framework that combines both qualitative and quantitative approaches to offer a nuanced understanding of the challenges hindering the widespread adoption of EMPs and their repercussions on the broader sustainability goals of construction projects. This research gap underscores the need for a more holistic and analytical exploration, which this study aims to address by employing a dual-method approach to unravel the complexities surrounding EMP adoption in the construction sector. Based on the above-mentioned literature this study assumed that: H1. The realization of OSS in building projects is significantly correlated with EMP barriers (Figure 1).

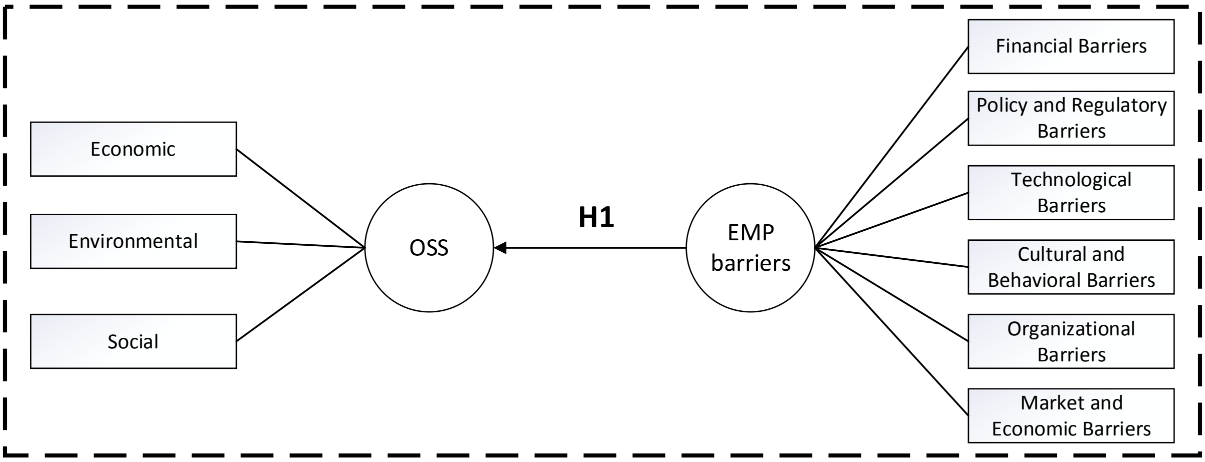

Figure 1. Hypothetical model

3. Research Methodology

The methodology of this study unfolds in three sequential steps, as shown in Figure 2. Firstly, it involves the identification of EMP barriers through an extensive literature review. Following this, the second step encompasses the development of survey questions and the collection of data from professionals engaged in construction projects in Saudi Arabia. Lastly, the study employs SEM and ANN analyses to discern crucial insights into the identified barriers and their underlying dimensions.

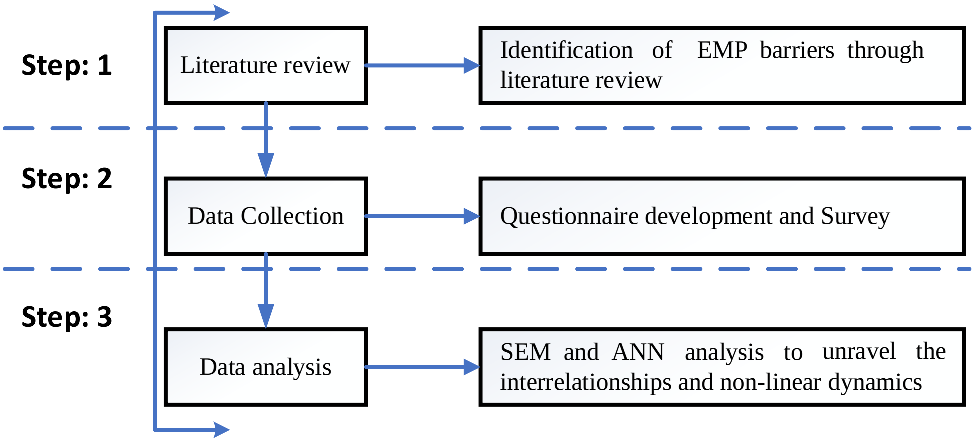

Figure 2. Research Framework

3.1. Identification of Barriers

The difficulties involved in implementing EMPs in the construction sector were thoroughly reviewed in this study. According to Ali et al. [56–58], the literature review thoroughly searched several databases, including ScienceDirect, Springer, Emerald Insight, Taylor & Francis, Google Scholar, JSTOR, and PubMed. Search terms including "barriers," "energy management," and "construction projects" were used in the beginning stages of the search to find more than two hundred publications. From a pool of 35 distinct publications, 85 pertinent papers were picked after a thorough screening procedure.

Following a thorough examination of the abstracts and content of these papers, some journals and publications that were judged unnecessary were removed from the final list. Thirty-nine papers from 23 sources, including one book and one conference, were included in the final edited collection. Among the esteemed journals that significantly influenced the research were Procedia Manufacturing, International Journal of Sustainable Building Technology and Urban Development, Journal of Property Investment & Finance, Journal of Technology Management in China, Energy Policy, Journal of Energy, Procedia Engineering, Energy Conversion and Management, and Energy and Buildings. Based on the literature review, Table 1 methodically outlines the barriers to EMP adoption in building projects.

Table 1. List of barriers to EMP in construction projects

Categories	Barriers	Code	References
Financial Barriers (FB)	The higher initial costs associated with adopting EMP.	Bar1	[27, 28, 37]
	Limited financing options, such as the absence of interest-free and long-term loans, for implementing energy management technology.	Bar2	[25, 26, 32, 59]
	Uncertain earnings and an extended payback period for EMP investments.	Bar3	[19, 20, 29, 31]
Policy and Regulatory Barriers (PRB)	Limited government incentives and support to encourage the adoption of EMP.	Bar4	[17, 18, 23, 24]
	Changes in energy management rules due to shifts in political governments.	Bar5	[13, 21, 22]
	The absence of EMP-based codes, rules, and regulations.	Bar6	[10-12]
Technological Barriers (TB)	Insufficient advancements in energy management technology, hindering innovation.	Bar7	[10, 11, 17]
	The absence of standardized metrics for measuring the performance of EMP initiatives.	Bar8	[10, 15, 16]
	Insufficient technical information and expertise related to EMP adoption.	Bar9	[4, 5, 14]
Cultural and Behavioral Barriers (CBB)	Resistance stemming from cultural, attitudinal, and behavioral factors impeding EMP adoption.	Bar10	[2, 3, 8, 9]
	Lack of awareness regarding the benefits and adoption of EMP.	Bar11	[1, 6, 7, 60]
	Limited interest from clients and a lack of market demand for EMP adoption.	Bar12	[61-64]
	A lack of interest from developers in implementing EMP.	Bar13	[65-68]
Organizational Barriers (OB)	A lack of interest and support from top management in addressing energy management issues.	Bar14	[52, 69, 70]
	Insufficient communication and collaboration among project stakeholders regarding EMP initiatives.	Bar15	[49-51, 71]
	Delays in decision-making processes related to EMP initiatives.	Bar16	[44, 55, 72]
Market and Economic Barriers (MEB)	Absence of specific conditions for implementing EMP on construction sites.	Bar17	[41-43, 48]
	Insufficient training and education on EMP and sustainable construction practices.	Bar18	[45-47]
	Volatility in the prices of energy resources and carriers affecting EMP implementation.	Bar19	[35, 36, 40]
OSS	Environmental	OSS1	
	Social	OSS2	
	Economic	OSS3	

3.2. Survey Design and Administration

We carefully designed a questionnaire to survey the obstacles to deploying EMPs in the construction industry. There were two main sections to the questionnaire: In Part 1, background data was gathered, and respondents' demographic profiles and jobs in the construction sector were examined. It sought to ascertain the frequency of exposure to incidents relevant to the deployment of EMPs. In Part 2, the adoption of EMPs in the construction industry was examined, and respondents were asked to rank these challenges on a Likert scale of 1 to 5. This scale included technical and soft skills evaluations, ranging from "not important" to "very important."

Senior people with research and industry experience in EMP thoroughly reviewed and revised the final sets of questionnaires before they were sent. The fundamental criterion for selecting appropriate respondents for this study was the inclusion of experts actively involved in maintenance projects within the Saudi Arabia construction sector. A combination of purposive and snowball sampling techniques—non-probability methods—was used to target this audience. The study team used their contacts and industry experience to find participants affiliated with construction companies through purposeful sampling. Purposive sampling, as opposed to probability sampling procedures, adds some researcher bias, although it is justified without a sample frame [73]. Potential participants were emailed an online survey using the "Google Forms" tool. As an additional tactic, the "snowball technique" was employed to get respondents to share the survey link with acquaintances who would be beneficial sources of information for the study [74]. Email reminders were sent out regularly to encourage member participation. In the end, 106 replies were received; however, six were rejected because of too many missing data points. The remaining 100 responses were subjected to data analysis, which gave our investigation into the obstacles to EMP adoption in the Saudi Arabia construction industry a firm basis.

3.3. Data Analysis

3.3.1. SEM Analysis and Model Development

SEM is a multivariate analysis method that takes into account both econometric and psychometric points of view, according to Wong [75]. Numerous academic fields, including construction management [76], management, organizational behavior [77], construction management [78] and so on, have made extensive use of SEM. Factor analysis and multiple regression modeling are successfully combined in SEM. Using a straightforward method, researchers can replicate in a single analysis the links between latent variables (constructs) generated by visible variables (measurement items) [79]. SEM is frequently used to identify modeling and computational errors as well as to assess many interdependent connections. Therefore, the observed variables were computed, and a thorough assessment of data assumptions was carried out in accordance with substantive/theoretical and methodological issues. Scientists may develop a model, watch it work, and analyze all the relationships and correlations found in the data by using SEM [80]. PLS-SEM is another term for the component-based approach. In exploratory research, it is mostly utilized to develop concepts and theories [81]. PLS-SEM can help avoid making restrictive assumptions that are necessary for a thorough evaluation of the highest likelihood of theories [82]. The sustainability pillars have been the subject of additional research [83]. Project methodology and strategic sustainability goals could be hard to change [84]. Waqar et al. [85] assert that social sustainability, economic feasibility, and environmental concerns must all be balanced. Finding practical ways to integrate sustainability into contemporary workplaces has become more important as the building industry's interest in the concept has grown [86]. The expanded use of EMP in the early phases of planning may be motivated by the need for sustainable growth and the creative approach to corporate social responsibility that firms have adopted. The environmental, economic, and social pillars of sustainability are comparable to the function that EMP serves in the building process, claim Oke et al. [87]. However, through expert interviews, six major clusters of implementation-related hurdles were found, and these clusters matched the ideas and measurement systems outlined in (Perno et al., 2022) (see Figure 2). Furthermore, this study revealed that:

The SEM technique was employed to examine the impact of EMP barriers on OSS. The correlations between different elements are shown by the SEM approach [88]. This study used a SEM technique to investigate the relationship between OSS and lowering EMP barriers. The results show a link between each concept and the given indicators [89]. According to Zhang et al. (2019), the procedure is based on equations and has arbitrary factors and structural limitations [32]. According to Teng et al. [90], SEM is becoming more and more recognized as a methodology for non-experimental research, and hypothesis analysis approaches were not always adequately controlled. Using reflective and formative features of the Partial Least Square (PLS) model, the relationship between OSS and reducing barriers to EMP has been investigated. However, in order to do the PLS-SEM analysis in this work, three crucial evaluations were used: the measurement model, the structural model, and the common method variance. PLS-SEM is a popular route model that can connect independent and dependent components [91].

- Common Methods Variance (CMV)

From the Common Methods Variance (CMV) [87], the CMB was created. Clarification of the mistake examination's conclusions is a goal of CMB, as the data collection approach could lead to trigger difficulties [92]. It is essential to identify any CMV in order to comprehend these issues and challenges. Thus, a formal, methodical study of a single component was used, in line with Harman's conclusions [93].

- Measurement model

The relationship between the measurements and their construct is made clearer by the measurement model [94]. One may consider the analysis and assessment of the measurement model to be a validation process [94]. While evaluating the applicability of particular measurement sets, PLS keeps a running list of related ideas. Assessments of "(1) indicator reliability, (2) composite reliability (c_r), (3) average variance extracted (AVE), and (4) discriminant validity" are required in order to examine the reflective model (first order), according to Munianday et al. [95] Cronbach's alpha, sometimes called the consistency or dependability coefficient [95], is a measure of how well a collection of questions analyzes a single, one-dimensional idea. The expression for Cronbach's alpha (α) is as follows [96]:

$$\alpha = \frac{\mathrm{N}-\bar{r}}{1+(\mathrm{N}-1)-\bar{r}} \tag{1}$$

where r is the mean relationship between the items and N is the number of matters. Considering the documented variations in Cronbach alpha's performance, a confirmatory approach to reliability measurement must be taken into account [95]. Composite dependability (ρ_c) yields a more reliable statistic, claims [97]. According to Durdyev et al. [94], values of ρ_c more than 0.7 are required for all kinds of research, whereas 0.6 is a reasonable cutoff point for exploratory investigations. According to Durdyev et al. [94], the expression for composite reliability is as follows:

$$\rho_c = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum \mathrm{var}\,(\varepsilon_i)} \tag{2}$$

In this case, var(ε_i) = 1 − λ², i, ρ_c denotes the composite reliability score, and λ_i denotes each item's component loading to a latent construct. When calculating Cronbach's alpha, the factor loadings of each item are ignored. However, because the composite reliability makes use of the item loadings identified within the theoretical model, it performs better than Cronbach's alpha [98]. Furthermore, the average retrieved AVE was used to evaluate the latent variables' convergent validity [99]. The widely recognized AVE metric can be used to demonstrate the convergent validity of the model's component elements. The formula for AVE is as follows:

$$AVE = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum \mathrm{var}\,(\varepsilon_i)} \tag{3}$$

AVE stands for the average variance extracted, while var(ε_i) = 1 − λ², i indicates how each item is loaded onto a latent construct. Furthermore, research has been done to examine discriminant validity. Conceptually, each construct is evaluated [98]. The goal is to confirm that the studied notion is empirically distinct or unique [95].

- Model structural

One of the most important techniques for concurrently analyzing all intricate relationships between constructs was proposed: the structural model. In a similar vein, Durdyev et al. [94] employed it to create the structural model that evaluated the effect of EMP barriers on OSS. The two main approaches that form the basis of the structural model used in this study are as follows:

According to Durdyev et al. [94], the primary focus of a collinearity analysis is the extent to which other factors may predict or account for the effects of a variable. The main problem is that the informative measures of indicator weights may be misrepresented by collinearity [99]. Furthermore, bootstrap standard errors resulting from collinearity may raise and trigger mistakes dramatically. The variation Inflation Factor (VIF), which indicates how frequently more indicators of the same construct might address an indicator's variation, is used to measure collinearity. According to Awang et al. [98], in order to receive the PLS algorithm test report in the Smart PLS 4.0 software, VIF needs to be lower than the recommended threshold level 5.

Rather than using parametric assumptions, the bootstrapping methodology approximates the variance of data points among sub-samples. A resampling method for sampling analysis is called bootstrapping. One large data set is divided into multiple sample sizes, and a smaller number of related statistical data (expressed as structural or regression coefficients) are measured. This study proposed a causal relationship between (OSS) and £ (EMP barriers). As a result, "in this case, the internal relationship—the relationship between the £, μ, and €1 equation in the structural model—can be expressed as a linear equation as shown below" [95]:

$$\mu = \beta\, £ + €1 \tag{4}$$

where residual variance (€1) and the path coefficient (β) are expressed. Consequently, the weight of a standardized regression analysis and a multiple regression analysis are comparable.

3.3.2. ANN Analysis

Artificial neural network analysis not only advances knowledge through learning mechanisms but also provides insight into how synapses and neurons function in the brain [78, 100]. By using machine learning approaches, ANN analysis enables researchers to forecast the significance of antecedents [101]. Furthermore, ANN makes it easier for researchers to validate and enhance PLS-SEM data. To address the problem of non-linearity and linearity between the constructs, Wong et al. [102] provide a hierarchy of constructs and a grading system based on sensitivity analyses [103]. The following are the formulas for activation functions:

$$\text{Distinctiveness (Linear) } (x) = x \tag{5}$$

$$\text{Hyperbolic Tangent tanh } (x)\mathrm{f_x} = \frac{2}{1+e^{-2x}} - 1 \tag{6}$$

$$\text{Sigmoid factor } \mathrm{f_x} = \frac{2}{1+e^{-x}} \tag{7}$$

Additionally, studies have demonstrated that ANNs perform better in terms of accuracy and outcome reliability than SEMs or multi-step regressions. Thus, it is reasonable to conclude that studies employing PLS-SEM and ANN are complementary [78]. Furthermore, there have been suggestions that ANNs mimic the way that information travels through human brains. The three roles of artificial neural networks (ANNs) are the transfer function, network design, and learning rules [100]. Subcategories such as feed-forward multilayer perceptrons [78], recurrent networks [100] and radial basis networks [102] are also included in these functions. Researchers most often use three layers: inputs, outputs, and hidden neurons, in addition to feed-forward multilayer perceptrons (MLPs) [102]. Independent variables often represent the input layer. These parts gather unprocessed information and send it to buried neurons as synaptic weights. An output neuron represents the dependent variable in a model. Apart from the activation function, extensive research has been conducted on the sigmoid function [78]. Moreover, multilayer neural network models are widely recognized as substantial and dependable, and they can manage complex problems in higher-order models. Multilayer perceptron neural networks were utilized for both training and testing of the suggested model.

4. Results

This section of the paper presents the results of the demographic information of surveyed participants, barriers to EMP use in construction projects, and exploratory factor analysis on barriers to EMP use in construction projects amongst construction companies.

4.1. Demographic Details of the Survey Participants

Table 2 provides a comprehensive overview of the demographic characteristics of the 100 respondents in the study. The respondents were categorized based on several key variables. Regarding work experience, 19% of participants had less than five years, 27% had 5–10 years, 16% had 11–15 years, 22.7% had 16–25 years, and 15.3% had more than 25 years of experience. The professional field distribution included 26.7% architects, 30.7% civil engineers, 18.6% electrical engineers, 16% mechanical engineers, and 8% quantity surveyors. Current positions varied among the respondents, with 6% holding director positions, 9.3% being senior managers, 30% being managers, 18.7% being design engineers, and 36% being site engineers. Regarding educational attainment, 10% had diplomas, 15% had bachelor's degrees, 20% had M.Sc. degrees, 50% held Ph.D. degrees, and 5% had other educational qualifications. The respondents' organizational functions were distributed across client roles (40%), consultants (20%), and contractors (40%). This detailed breakdown provides a comprehensive snapshot of the diverse demographic characteristics within the respondent pool, offering valuable insights for the study's analysis and interpretation.

Table 2. Demographics details of the respondents

Variable	Characteristics	Percentage (%)
Work experience (Years)	Less than five	19
	5–10	27
	11–15	16
	16–25	22.7
	More than 25	15.3
Professional field	Architect	26.7
	Civil Engineer	30.7
	Electrical Engineer	18.7
	Mechanical Engineer	16
	Quantity surveying	8
Current position	Director	6
	Senior Manager	9.3
	Manager	30
	Design Engineer	18.7
	Site Engineer	36
Educational level	Diploma	10
	Bachelor's degree	15
	M.Sc.	20
	Ph.D.	50
	Others	5
Organization function	Client	40
	Consultant	20
	Contractor	40

4.2. SEM Results

4.2.1. Common Method Bias

To determine the variance of the conventional method, a single component analysis was conducted on the proposed model [92]. Research has shown that when the overall variation of the variables is less than fifty percent, the normal process bias does not affect the results that are obtained [95]. Because the common method variance is less than 50%, the study's conclusions—which showed that the first set of components accounted for 38.43% of the overall variance cannot be altered [104].

4.2.2. Measurement Model Assessment

4.2.2.1. Convergent Validity Analysis

The measurement model considers the degree of alignment and coherence between two or more measurements (barriers) of the same notion [105]. Construct validity is assessed using the measurement model. According to Munianday et al. [95], the following tests can be used with PLS-SEM to evaluate the convergent validity of the proposed constructs: "composite reliability scores (ρ_c), Cronbach's Alpha (α), and Average Variance Extracted (AVE)". Durdyev et al. [94] reported that Table 1 showed that every OSS and EMP barrier had a composite reliability greater than 0.60, suggesting acceptance. Table 1 indicates that the Cronbach Alpha was, nevertheless, 0.60.

Consequently, the evidence by Durdyev et al. [94] suggests a medium to high degree of reliability. The AVE was also used to evaluate the construct variables' convergent validity. A level of AVE larger than 0.5 is considered acceptable by Khan et al. [86], indicating that the measurement parameters account for at least 50% of the variation [106]. For every research construct, Table 3 shows the estimated AVE values, which are greater than 50%. These findings demonstrated the convergence and internal stability of the measurement model. It also meant that the measurement components did not quantify any other construct in the study model for any construct that was thoroughly measured. Chen et al. [107] note that while an external load score of 0.70 is optimal, scores of 0.50 or higher are nevertheless acceptable, provided the analysis explains. All measurements from the first model outdoor loads are shown in Table 4 and Figure 3. All outside loads are acceptable, with the exception of Bar14, which was removed from the original model because of a poor loading of less than 0.5 [108]. It demonstrated their minimal effect on linked structures. The evaluation of the modified model following the removal of these observations is shown in Table 4 and Figure 4.

Table 3. Measurement model of barriers to adopt EMP

Categories	Code	Outer loading	Cronbach's Alpha α	Composite Reliability ρ_c	AVE
Financial Barriers (FB)	Bar1	0.965	0.841	0.894	0.681
	Bar2	0.68			
	Bar3	0.915			
Policy and Regulatory Barriers (PRB)	Bar4	0.963	0.973	0.982	0.948
	Bar5	0.81			
	Bar6	0.97			
Technological Barriers (TB)	Bar7	0.837	0.917	0.948	0.859
	Bar8	0.804			
	Bar9	0.895			
Cultural and Behavioral Barriers (CBB)	Bar10	0.68	0.944	0.973	0.947
	Bar11	0.915			
	Bar12	0.846			
	Bar13	0.843			
Organizational Barriers (OB)	Bar15	0.877	0.902	0.933	0.823
	Bar16	0.905			
Market and Economic Barriers (MEB)	Bar17	0.957	0.905	0.941	0.841
	Bar18	0.864			
	Bar19	0.957			
OSS	OSS1	0.954	0.837	0.883	0.716
	OSS2	0.772			
	OSS3	0.982			

Table 4. Discriminant validity (HTMT)

Constructs	CBB	FB	MEB	OB	OSS	PRB	TB
CBB							
FB	0.371						
MEB	0.380	0.031					
OB	0.313	0.066	0.090				
OSS	0.414	0.019	0.075	0.073			
PRB	0.634	0.372	0.383	0.163	0.387		
TB	0.835	0.268	0.267	0.213	0.336	0.542	

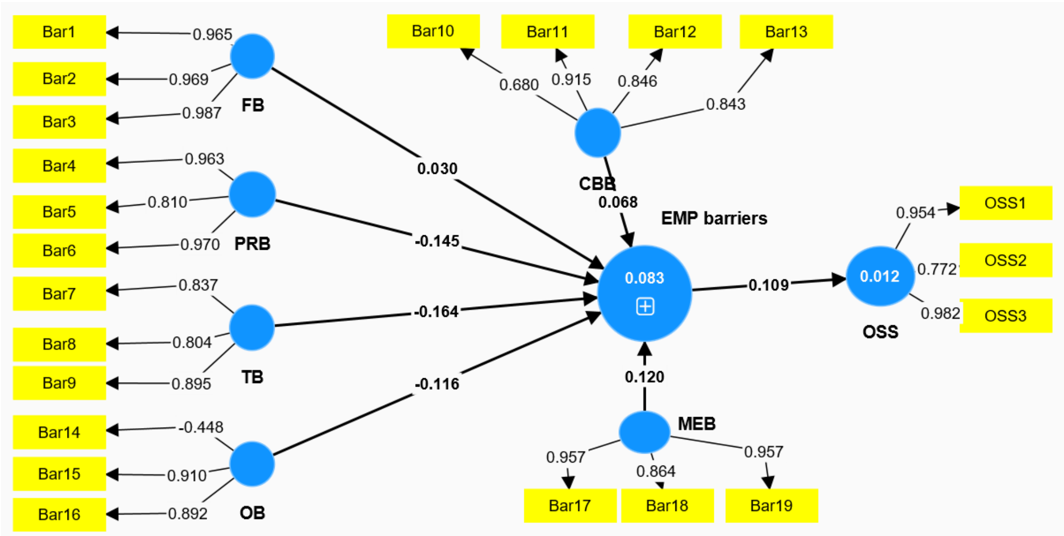

Figure 3. Initial Model

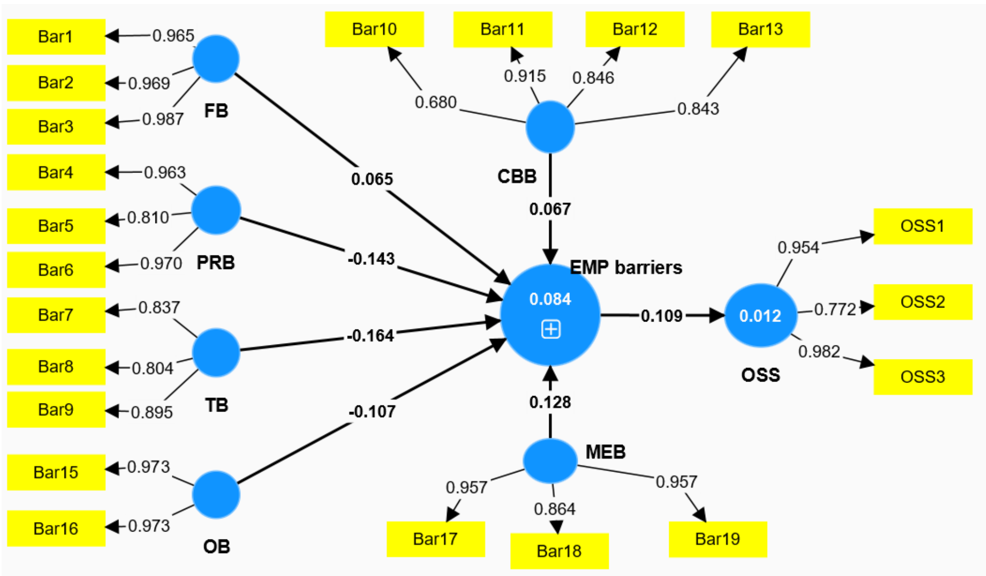

Figure 4. Final Model

4.2.3. Discriminant Validity Assessment

The application of discriminant validity evaluation in SEM research is growing [104]. It validates the concept's originality or empirical differentiation [105]. This study uses cross-loadings, the Hetrotrait-Monotrait Criterion Ratio (HTMT), and the Fornell-Larcker criteria to evaluate discriminant validity. Table 4's statistics show that the Fornell and Larcker technique is used to recognize and approve the discriminant validity of the OSS components and EMP barriers, as per Wong et al. [102]. This is due to the fact that the correlation between the variables and construct indicators should be greater than the average variance extracted (AVE) square root. An additional technique for assessing discriminant validity in variance-based structural equation modeling (SEM) is the HeterotraitMonotrait (HTMT) criterion ratio.

The HTMT technique ascertains the precise correlation between two constructs, assuming accurate measurement. Using the HTMT technique, Kar and Jha [106] proposed variance-based structural equation modeling (SEM) to evaluate discriminant validity. When the score is between 0.85 and 0.90, there is a difference between the two constructs. If there are conceptual parallels between the conceptions, the score should be less than 0.90; if not, it should be less than 0.85. Table 3 displays the HTMT values for the components that are the subject of the inquiry. The results provide adequate evidence of discriminant validity. The cross-loading method was used to evaluate the discriminant validity of OSS components and EMP barriers, respectively. According to Wong et al. [102], it establishes if a variable has a higher cross-loading than any other on a latent construct (derived from other concepts). The loadings on the structures that are highlighted in Table 5 are greater than the loadings on the other constructs. (one after the other). Thus, it is possible to confirm that each build is one-dimensional.

Table 5. Cross loadings results

Items	CBB	FB	MEB	OB	OSS	PRB	TB
Bar1	0.303	0.965	0.908	-0.081	0.93	0.357	0.206
Bar2	0.68	0.112	0.046	0.101	0.118	0.379	0.464
Bar3	0.915	0.312	0.326	0.312	0.346	0.448	0.614
Bar4	0.846	0.33	0.327	0.15	0.353	0.561	0.558
Bar5	0.843	0.356	0.355	0.344	0.337	0.416	0.552
Bar6	0.271	-0.075	-0.105	0.973	-0.076	0.118	0.192
Bar7	0.255	-0.045	-0.057	0.973	-0.045	0.18	0.207
Bar8	0.315	0.982	0.957	-0.079	0.984	0.357	0.209
Bar9	0.26	0.686	0.864	-0.073	0.715	0.239	0.161
Bar10	0.315	0.982	0.957	-0.079	0.984	0.357	0.209
Bar11	0.363	0.969	0.903	-0.026	0.949	0.302	0.243
Bar12	0.299	0.987	0.956	-0.078	0.982	0.351	0.192
Bar13	0.535	0.3	0.297	0.151	0.314	0.963	0.467
Bar 15	0.506	0.296	0.315	0.102	0.299	0.81	0.415
Bar 16	0.478	0.36	0.34	0.162	0.336	0.97	0.417
Bar 17	0.723	0.262	0.258	0.158	0.309	0.449	0.837
Bar 18	0.611	0.231	0.225	0.13	0.247	0.375	0.804
Bar 19	0.497	0.141	0.125	0.205	0.164	0.401	0.895
OSS1	0.397	0.912	0.857	-0.026	0.954	0.293	0.297
OSS2	0.294	0.721	0.863	-0.081	0.772	0.301	0.249
OSS3	0.299	0.987	0.956	-0.078	0.982	0.351	0.192

4.2.4. Structural Model Assessment

4.2.4.1. Collinearity Analysis

Formative assessment models frequently show unexpectedly high correlations between measurements; in the meantime, the study's notions of the EMP barriers were formative. Every VIF result was less than 3.5. It implied that each of these concepts caused DT's challenges. Table 6 displays the significant route coefficient β for six first-order subscales related to EMP barriers: Financial, Policy and Regulatory, Technological, Cultural and Behavioral, Organizational, Market, and Economic.

Table 6. Formative constructs analysis

Paths	β	SD	P Values	VIF
CBB → EMP barriers	0.213	0.047	0	1.861
FB → EMP barriers	0.07	0.031	0	1.831
MEB → EMP barriers	0.178	0.048	0	1.149
OB → EMP barriers	0.821	0.027	0	1.133
PRB → EMP barriers	0.437	0.057	0	1.19
TB → EMP barriers	0.179	0.033	0	1.187

4.2.4.2. Bootstrap Analysis Evaluation

The investigation's validation of the proposed research hypothesis was a notable feature. The model hypothesis's significance was evaluated using the bootstrapping technique [109]. The route coefficient, which expresses the degree to which one path influences another, is represented by the value of each path [94]. The SmartPLS 4.0.9.9 software now includes a bootstrapping method for calculating the route coefficient errors for CFA. Therefore, to establish the t-statistics for proposition testing, 5000 subsamples were used to validate a suggestion by Cruz-Jesus et al. [110]. There is only one structural equation that explains the fundamental relationships between the constructs and Equation 1 in the PLS Model, and it also provides a workaround for EMP barriers.

Consequently, standardized p-values for the endogenous construct and route significance were scrutinized to construe the results of the bootstrapping investigation [106]. These results showed that OSS and getting past EMP hurdles had a significant and positive influence (=0.109, p = 0.000) (see Table 7). OSS and overcoming the EMP barriers are the two most important aspects of this study, and they both function similarly.

Table 7. Path analysis

Paths	β	SD	P Values	VIF
EMP barriers → OSS	0.109	0.078	0	1.128

4.2.4.3. The Structural Model's Explanatory Power (R2)

One of the most crucial assessments in PLSSEM is evaluating the R2 for the OSS [84]. In this study, the exogenous construct was found to be capable of explaining 19.6% of OSS, with OSS serving as the dependent variable. The R2 and adjusted R2 values of 0.012 demonstrated this. According to these results, the EMP barrier size is appropriate and has minimal impact [111].

4.3. ANN Results

This study used the major factors of the SEM-PLS path analysis as the input neurons in the ANN model, using a similar technique to that used by Arpaci et al. [112] (Figure 4). Large datasets with complicated nonlinear correlations can be efficiently captured by artificial neural networks (ANNs). Before using ANNs, linear approaches must be used to simplify the data and identify important variables. Artificial neural networks (ANNs) increase prediction and classification accuracy by identifying patterns that linear approaches can miss. Prior to utilizing ANNs, it was required to identify pertinent variables through the use of a linear technique in the earliest phases of data processing. Once key variables were found, artificial neural networks (ANNs) aided in the analysis of complex interactions. When there are nonlinear interactions between the exogenous and endogenous variables and the data are not regularly distributed, artificial neural networks (ANNs) can be used.

ANNs are also resistant to noise, outliers, and small sample sizes. The model can enable non-compensatory models, which are similar to compensatory models in that they don't need to raise one element to offset a decline in another [100]. An artificial neural network (ANN) was conducted using IBM's SPSS neural network module. A normal distribution is not necessary for the artificial neural network (ANN) method to capture both linear and nonlinear interactions. A feed-forward-backward-propagation (FFBP) algorithm uses training to estimate errors in the backward direction while feeding inputs in the forward direction to anticipate the result of an investigation [78]. Using a multilayer perceptron and the sigmoid activation function, the input and hidden layers were built. Prediction accuracy can be increased and mistakes reduced by employing multiple learning cycles. The remaining samples were used for training, and the remaining 90% of the samples were used for testing [113]. To prevent overfitting, the root means square error (RMSE) was calculated using ten-fold cross-validation [114]. To assess the model's prediction accuracy, the RMSE of the training data, the RMSE of the testing data, the mean, and the standard deviation were looked at (refer to Figure 5).

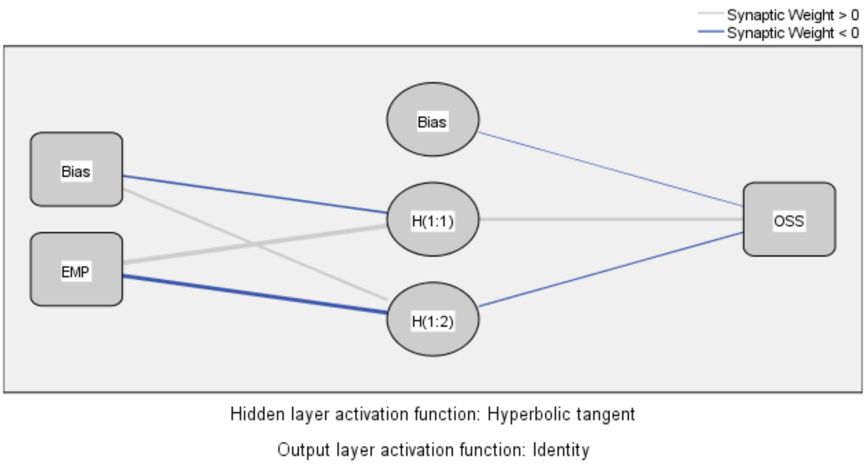

Figure 5. Model prediction

The training and testing procedures' RMSE values—0.698 and 0.663, respectively—are comparatively low, as Table 8 and Figure 6 demonstrate. We were able to verify that the model accurately reflected the data. We examined the R^2 value of the ANN model in accordance with the work of Loh et al. [115] and discovered that it predicted EMP barriers for OSS with an accuracy of 100%.

Table 8. RMSE values of the training and testing

Neural network	Model Input: EMP barriers; Output: OSS	
	Training	Testing
	RMSE	RMSE
ANN1	0.698	0.668
ANN2	0.710	0.658
ANN3	0.701	0.722
ANN4	0.704	0.716
ANN5	0.729	0.664
ANN6	0.698	0.734
ANN7	0.763	0.703
ANN8	0.704	0.663
ANN9	0.698	0.750
ANN10	0.702	0.695
Mean	0.710	0.697
SD	0.021	0.033

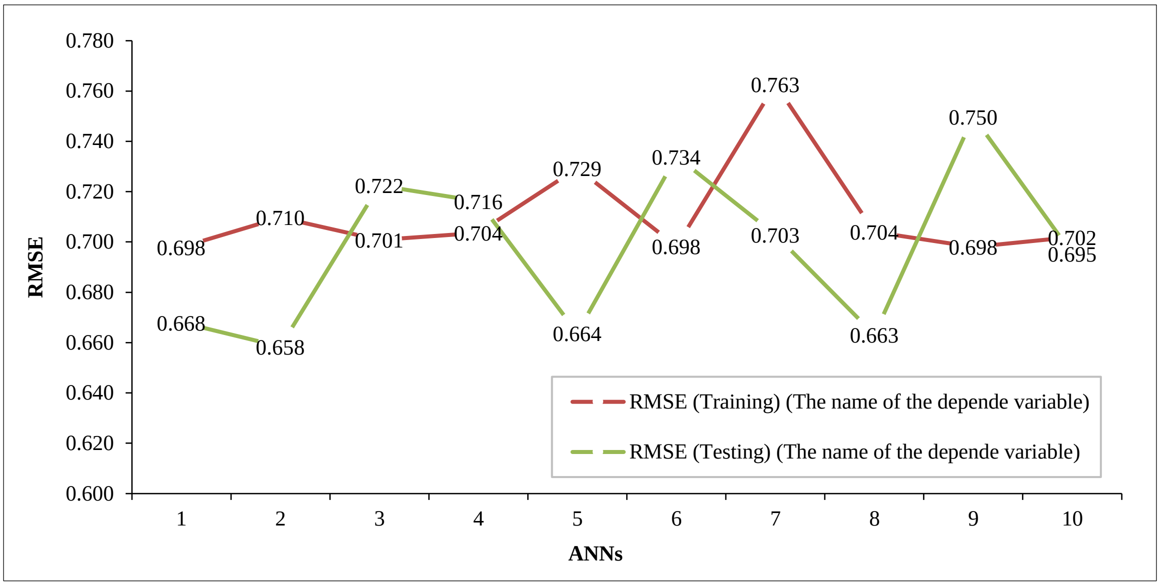

Figure 6. RMSE statistics

To ascertain how effectively each input neuron predicted events, a sensitivity analysis was performed. By dividing the relative importance of each input neuron by the greatest value, we were able to obtain its normalized importance, which we then displayed as a percentage [116]. The EMP barriers have a normalized relevance of 100% among the predictors.

5. Discussion

The investigation into barriers impeding the implementation of EMPs within the construction industry reveals a multifaceted landscape shaped by financial, policy and regulatory, technological, cultural and behavioral, and organizational constraints. Financial barriers, encompassing higher initial costs (Bar1: 0.965), limited financing options (Bar2: 0.68), and uncertain earnings (Bar3: 0.915), stand out as formidable obstacles, potentially impeding organizations from embracing sustainable practices [34, 36, 66, 71]. These financial hurdles underscore the challenges associated with funding sustainable initiatives and emphasize the need for innovative financial models and governmental support. Similarly, policy and regulatory challenges, such as limited government incentives (Bar4: 0.963), dynamic energy management rules influenced by political shifts (Bar5: 0.81), and the absence of EMP-specific codes and regulations (Bar6: 0.97), contribute to an environment of uncertainty surrounding sustainable initiatives [38, 43, 50, 51, 55]. The high outer loadings indicate the significant impact of these challenges, highlighting the importance of advocating for consistent regulatory support and the development of dedicated codes for EMPs.

The technological dimension presents barriers rooted in insufficient advancements (Bar7: 0.837), the absence of standardized metrics (Bar8: 0.804), and a lack of technical expertise (Bar9: 0.895), collectively hindering innovation in energy management within the construction sector [61, 69, 70]. The high outer loadings suggest that technological barriers pose a substantial challenge, emphasizing the need for investments in research and development and capacity building. Cultural and behavioral factors manifest as resistance (Bar10: 0.68), lack of awareness (Bar11: 0.915), and limited interest from clients and developers (Bar12: 0.846, Bar13: 0.843), underscoring the importance of a cultural shift toward sustainable practices [36, 53, 60, 68, 72]. The substantial outer loadings indicate that addressing these cultural and behavioral challenges is pivotal for successful EMP implementation. Organizational barriers, including a lack of top management support (Bar14: 0.877), insufficient communication (Bar15: 0.905), and delays in decision-making (Bar16: 0.863), emphasize the need for comprehensive organizational strategies to drive sustainability initiatives [33, 51, 67]. The high outer loadings highlight the organizational challenges, requiring a concerted effort to foster commitment and streamline decision-making processes.

Addressing these barriers necessitates a multifaceted approach that integrates innovative financial strategies, advocacy for regulatory support, investments in technology and capacity building, cultural transformation programs, and organizational commitment. Drawing from insights gleaned from previous studies [3, 4, 35, 72], it is evident that a holistic response is essential to overcoming the challenges hindering the implementation of Energy Management Programs (EMPs) in the construction industry. By collaborating with industry stakeholders, policymakers, and organizations [28, 34, 59, 68], concerted efforts can be made to create an environment conducive to sustainable energy practices, facilitating a transformative shift in the sector. Furthermore, the specific values of the outer loadings obtained from empirical analyses provide a quantitative understanding of the relative impact of each barrier, thereby guiding targeted interventions for effective EMP implementation.

5.1. Implications

5.1.1 Theoretical Implications

The research presents a robust theoretical approach by introducing a comprehensive model that addresses various dimensions of barriers to Energy Management Practices (EMPs) adoption within the construction industry. This model encompasses financial, policy and regulatory, technological, cultural and behavioral, organizational, and market and economic dimensions, providing a holistic perspective on the challenges hindering EMP integration. By meticulously quantifying the impact of each barrier, the study offers a nuanced understanding of their relative importance, thereby contributing valuable insights for researchers.

This theoretical approach allows for a more informed view of the varying degrees of influence that different factors exert on the adoption of sustainable practices. Specifically, it validates existing theoretical frameworks related to the adoption of innovative technologies in construction. The study empirically supports factors such as economic considerations, regulatory support, technological readiness, cultural alignment, organizational dynamics, and market conditions, all of which are highlighted in innovation adoption theories. By substantiating these theoretical constructs within the context of EMP adoption, the research provides a solid foundation for understanding and addressing barriers to sustainability within the construction industry. Thus, this theoretical approach not only advances our understanding of EMP adoption but also offers insights that can inform future research in sustainable construction practices.

5.1.2 Practical Implications

The identification and quantification of barriers in this study provide invaluable insights for industry stakeholders, policymakers, and project managers, facilitating strategic planning to overcome specific challenges and successfully integrate Energy Management Practices (EMPs) into construction projects. Addressing financial constraints, enhancing regulatory support, fostering technological innovation, and promoting cultural awareness emerge as key components of strategic plans for EMP adoption. The study suggests that resource allocation should be guided by the most influential barriers identified, allowing organizations and policymakers to prioritize efforts and resources effectively, thus maximizing the impact of interventions.

Moreover, the study highlights the importance of addressing technological and informational gaps through targeted training programs aimed at enhancing technical expertise and awareness among construction professionals. Policy-makers can leverage these insights to develop effective policies tailored to address identified barriers, including designing financial incentives, ensuring regulatory stability, and promoting technological innovation to facilitate EMP adoption. The empirical support provided by the study emphasizes the significance of these policy dimensions in fostering sustainability within the construction industry.

Furthermore, the study underscores the necessity of industry-wide collaboration and awareness campaigns to address cultural and behavioral barriers effectively. By engaging with stakeholders such as clients and developers, interest and demand for EMP adoption in construction projects can be enhanced. Additionally, the study emphasizes the interconnected nature of environmental, social, and economic factors in achieving Overall Sustainable Success (OSS) in construction projects. Practitioners can utilize this insight to align projects with broader sustainability goals, emphasizing not only economic viability but also environmental and social responsibility. This aligns with the growing global emphasis on sustainable and responsible business practices.

6. Conclusions

This study investigates the barriers impeding the implementation of Energy Management Programs (EMPs) in the construction industry through a dual-method approach, combining an extensive literature review with a targeted survey. The identified barriers encompass financial, policy and regulatory, technological, cultural and behavioral, and organizational dimensions. It is found that financial constraints, limited governmental support, technological inadequacies, cultural resistance, and organizational challenges collectively hinder the widespread adoption of EMPs in construction projects. Empirical validation through SEM and ANN analyses reinforces the significance of these barriers, offering insights into their interrelationships and relative importance. The findings emphasize the necessity of a holistic approach involving financial innovation, regulatory advocacy, technological advancements, cultural transformation, and organizational commitment to address these challenges effectively.

However, it is important to acknowledge the study's limitations. Primarily focusing on the construction industry in Saudi Arabia may limit the generalizability of the findings to other geographical locations or industries with distinct contextual factors. Although efforts were made to mitigate the response bias inherent in self-reported data from professionals engaged in construction maintenance projects through rigorous analyses, the potential for bias remains. Future research should expand the geographical scope to capture diverse industry contexts and assess the generalizability of identified barriers. Additionally, conducting longitudinal studies could offer insights into the dynamic nature of these barriers over time, providing a more nuanced understanding of their evolution. Exploring potential interventions and strategies to overcome these barriers would offer valuable insights to practitioners and policymakers aiming to promote sustainable practices in the construction sector.

Regarding the conclusion's suggestion of a holistic approach to addressing EMP adoption barriers, practical examples could include implementing comprehensive training programs to enhance cultural awareness and technical expertise among construction professionals. Additionally, fostering collaborative partnerships between industry stakeholders, policymakers, and educational institutions could facilitate knowledge sharing and innovation adoption. Organizational-level initiatives such as creating incentives for sustainable practices and fostering a culture of environmental responsibility could also play a crucial role in overcoming cultural and organizational challenges.

7. Declarations

7.1. Author Contributions

Conceptualization, Y.A., A.F.K., and M.A.; methodology, Y.A., A.F.K., and M.A.; software, Y.A., A.F.K., and M.A.; formal analysis, Y.A., A.F.K., and M.A.; investigation, Y.A., A.F.K., and M.A.; resources, Y.A. and A.F.K.; writing—original draft preparation, Y.A., A.F.K., and M.A.; writing—review and editing, Y.A., A.F.K., and M.A.; visualization, A.F.K. and M.A.; supervision, Y.A., A.F.K., and M.A.; funding acquisition, Y.A., A.F.K., and M.A. All authors have read and agreed to the published version of the manuscript.

7.2. Data Availability Statement

The data presented in this study are available in the article.

7.3. Funding

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7.4. Conflicts of Interest

The authors declare no conflict of interest.

8. References

[1] Jovanović, B., Filipović, J., & Bakić, V. (2015). Prioritization of manufacturing sectors in Serbia for energy management improvement - AHP method. Energy Conversion and Management, 98, 225–235. doi:10.1016/j.enconman.2015.03.107.

[2] Cagno, E., Trianni, A., Abeelen, C., Worrell, E., & Miggiano, F. (2015). Barriers and drivers for energy efficiency: Different perspectives from an exploratory study in the Netherlands. Energy Conversion and Management, 102, 26–38. doi:10.1016/j.enconman.2015.04.018.

[3] Shi, Q., Zuo, J., Huang, R., Huang, J., & Pullen, S. (2013). Identifying the critical factors for green construction - An empirical study in China. Habitat International, 40, 1–8. doi:10.1016/j.habitatint.2013.01.003.

[4] Shen, L. Y., & Tam, V. W. Y. (2002). Implementation of environmental management in the Hong Kong construction industry. International Journal of Project Management, 20(7), 535–543. doi:10.1016/S0263-7863(01)00054-0.

[5] Worrell, E., & Price, L. (2001). Policy scenarios for energy efficiency improvement in industry. Energy Policy, 29(14), 1223–1241. doi:10.1016/S0301-4215(01)00069-6.

[6] Zhang, X., Shen, L., & Chan, S. Y. (2012). The diffusion of solar energy use in HK: What are the barriers? Energy Policy, 41, 241–249. doi:10.1016/j.enpol.2011.10.043.

[7] Trianni, A., Cagno, E., & Worrell, E. (2013). Innovation and adoption of energy efficient technologies: An exploratory analysis of Italian primary metal manufacturing SMEs. Energy Policy, 61, 430–440. doi:10.1016/j.enpol.2013.06.034.

[8] Schleich, J., Gassmann, X., Faure, C., & Meissner, T. (2016). Making the implicit explicit: A look inside the implicit discount rate. Energy Policy, 97, 321–331. doi:10.1016/j.enpol.2016.07.044.

[9] Kangas, H. L., Lazarevic, D., & Kivimaa, P. (2018). Technical skills, disinterest and non-functional regulation: Barriers to building energy efficiency in Finland viewed by energy service companies. Energy Policy, 114, 63–76. doi:10.1016/j.enpol.2017.11.060.

[10] Palm, J., & Thollander, P. (2010). An interdisciplinary perspective on industrial energy efficiency. Applied Energy, 87(10), 3255–3261. doi:10.1016/j.apenergy.2010.04.019.

[11] Zhang, W., Wang, J., Liu, Y., Gao, G., Liang, S., & Ma, H. (2020). Reinforcement learning-based intelligent energy management architecture for hybrid construction machinery. Applied Energy, 275(5988), 115401. doi:10.1016/j.apenergy.2020.115401.

[12] Morel, J. C., Mesbah, A., Oggero, M., & Walker, P. (2001). Building houses with local materials: Means to drastically reduce the environmental impact of construction. Building and Environment, 36(10), 1119–1126. doi:10.1016/S0360-1323(00)00054-8.

[13] Verbeeck, G., & Hens, H. (2010). Life cycle inventory of buildings: A calculation method. Building and Environment, 45(4), 1037–1041. doi:10.1016/j.buildenv.2009.10.012.

[14] Karimpour, M., Belusko, M., Xing, K., & Bruno, F. (2014). Minimising the life cycle energy of buildings: Review and analysis. Building and Environment, 73, 106–114. doi:10.1016/j.buildenv.2013.11.019.

[15] Li, Y., Song, H., Sang, P., Chen, P. H., & Liu, X. (2019). Review of Critical Success Factors (CSFs) for green building projects. Building and Environment, 158(May), 182–191. doi:10.1016/j.buildenv.2019.05.020.

[16] Kang, J., Wang, L., Wang, Z., Zhang, J., & Dai, H. (2023). Improving the emergency management of energy infrastructure using scenario construction. International Journal of Hydrogen Energy, 48(23), 8731–8742. doi:10.1016/j.ijhydene.2022.11.208.

[17] Pelenur, M. J., & Cruickshank, H. J. (2012). Closing the Energy Efficiency Gap: A study linking demographics with barriers to adopting energy efficiency measures in the home. Energy, 47(1), 348–357. doi:10.1016/j.energy.2012.09.058.

[18] Lu, Y., Chang, R., Shabunko, V., & Lay Yee, A. T. (2019). The implementation of building-integrated photovoltaics in Singapore: drivers versus barriers. Energy, 168, 400–408. doi:10.1016/j.energy.2018.11.099.

[19] Golpîra, H., & Khan, S. A. R. (2019). A multi-objective risk-based robust optimization approach to energy management in smart residential buildings under combined demand and supply uncertainty. Energy, 170, 1113–1129. doi:10.1016/j.energy.2018.12.185.

[20] Wang, Y., Li, K., Zeng, X., Gao, B., & Hong, J. (2022). Energy consumption characteristics based driving conditions construction and prediction for hybrid electric buses energy management. Energy, 245, 123189. doi:10.1016/j.energy.2022.123189.

[21] Zhang, W., Wang, J., Xu, Z., Shen, Y., & Gao, G. (2022). A generalized energy management framework for hybrid construction vehicles via model-based reinforcement learning. Energy, 260(5988), 124849. doi:10.1016/j.energy.2022.124849.

[22] Zhang, Q. (2004). Residential energy consumption in China and its comparison with Japan, Canada, and USA. Energy and Buildings, 36(12), 1217–1225. doi:10.1016/j.enbuild.2003.08.002.

[23] Darko, A., Chan, A. P. C., Ameyaw, E. E., He, B. J., & Olanipekun, A. O. (2017). Examining issues influencing green building technologies adoption: The United States green building experts' perspectives. Energy and Buildings, 144, 320–332. doi:10.1016/j.enbuild.2017.03.060.

[24] Fernando, Y., & Hor, W. L. (2017). Impacts of energy management practices on energy efficiency and carbon emissions reduction: A survey of malaysian manufacturing firms. Resources, Conservation and Recycling, 126(July), 62–73. doi:10.1016/j.resconrec.2017.07.023.

[25] Nazeer Ahamed, M. F., & Mariappan, M. (2023). A study to determine human-related errors at the level of top management, safety supervisors & workers during the implementation of safety practices in the construction industry. Safety Science, 162(February), 106081. doi:10.1016/j.ssci.2023.106081.

[26] Ortiz, O., Castells, F., & Sonnemann, G. (2009). Sustainability in the construction industry: A review of recent developments based on LCA. Construction and Building Materials, 23(1), 28–39. doi:10.1016/j.conbuildmat.2007.11.012.

[27] Brunke, J. C., Johansson, M., & Thollander, P. (2014). Empirical investigation of barriers and drivers to the adoption of energy conservation measures, energy management practices and energy services in the Swedish iron and steel industry. Journal of Cleaner Production, 84(1), 509–525. doi:10.1016/j.jclepro.2014.04.078.

[28] Xue, X., Wu, H., Zhang, X., Dai, J., & Su, C. (2015). Measuring energy consumption efficiency of the construction industry: The case of China. Journal of Cleaner Production, 107, 509–515. doi:10.1016/j.jclepro.2014.04.082.

[29] Persson, J., & Grönkvist, S. (2015). Drivers for and barriers to low-energy buildings in Sweden. Journal of Cleaner Production, 109, 296–304. doi:10.1016/j.jclepro.2014.09.094.

[30] Chan, A. P. C., Darko, A., Olanipekun, A. O., & Ameyaw, E. E. (2018). Critical barriers to green building technologies adoption in developing countries: The case of Ghana. Journal of Cleaner Production, 172, 1067–1079. doi:10.1016/j.jclepro.2017.10.235.

[31] Darko, A., Chan, A. P. C., Yang, Y., Shan, M., He, B. J., & Gou, Z. (2018). Influences of barriers, drivers, and promotion strategies on green building technologies adoption in developing countries: The Ghanaian case. Journal of Cleaner Production, 200, 687–703. doi:10.1016/j.jclepro.2018.07.318.

[32] Zhang, Q., Oo, B. L., & Lim, B. T. H. (2019). Drivers, motivations, and barriers to the implementation of corporate social responsibility practices by construction enterprises： A review. Journal of Cleaner Production, 210, 563-584. doi:10.1016/j.jclepro.2018.11.050.

[33] Martek, I., Hosseini, M. R., Shrestha, A., Edwards, D. J., & Durdyev, S. (2019). Barriers inhibiting the transition to sustainability within the Australian construction industry: An investigation of technical and social interactions. Journal of Cleaner Production, 211(2019), 281–292. doi:10.1016/j.jclepro.2018.11.166.

[34] Maqbool, R., Arul, T., & Ashfaq, S. (2023). A mixed-methods study of sustainable construction practices in the UK. Journal of Cleaner Production, 430(August), 139087. doi:10.1016/j.jclepro.2023.139087.

[35] Fu, C., Liu, Y. Q., & Shan, M. (2023). Drivers of low-carbon practices in green supply chain management in construction industry: An empirical study in China. Journal of Cleaner Production, 428(October), 139497. doi:10.1016/j.jclepro.2023.139497.

[36] Pietrosemoli, L., & Rodríguez Monroy, C. (2013). The impact of sustainable construction and knowledge management on sustainability goals. A review of the Venezuelan renewable energy sector. Renewable and Sustainable Energy Reviews, 27, 683–691. doi:10.1016/j.rser.2013.07.056.

[37] Karatayev, M., Hall, S., Kalyuzhnova, Y., & Clarke, M. L. (2016). Renewable energy technology uptake in Kazakhstan: Policy drivers and barriers in a transitional economy. Renewable and Sustainable Energy Reviews, 66, 120–136. doi:10.1016/j.rser.2016.07.057.

[38] Hesselink, L. X. W., & Chappin, E. J. L. (2019). Adoption of energy efficient technologies by households – Barriers, policies and agent-based modelling studies. Renewable and Sustainable Energy Reviews, 99, 29–41. doi:10.1016/j.rser.2018.09.031.

[39] Liu, H., Xing, X., Shang, W., & Li, T. (2021). NSGA-II Optimized Multiobjective Predictive Energy Management for Fuel Cell/Battery/Supercapacitor Hybrid Construction Vehicles. International Journal of Electrochemical Science, 16(4), 1–16. doi:10.20964/2021.04.24.

[40] Umar, U. A., Shafiq, N., & Ahmad, F. A. (2021). A case study on the effective implementation of the reuse and recycling of construction & demolition waste management practices in Malaysia. Ain Shams Engineering Journal, 12(1), 283–291. doi:10.1016/j.asej.2020.07.005.

[41] Davies, P. J., Emmitt, S., & Firth, S. K. (2015). Delivering improved initial embodied energy efficiency during construction. Sustainable Cities and Society, 14(1), 267–279. doi:10.1016/j.scs.2014.09.010.

[42] Gupta, P., Anand, S., & Gupta, H. (2017). Developing a roadmap to overcome barriers to energy efficiency in buildings using best worst method. Sustainable Cities and Society, 31, 244–259. doi:10.1016/j.scs.2017.02.005.

[43] Moglia, M., Cook, S., & McGregor, J. (2017). A review of Agent-Based Modelling of technology diffusion with special reference to residential energy efficiency. Sustainable Cities and Society, 31, 173–182. doi:10.1016/j.scs.2017.03.006.

[44] Caputo, P., & Pasetti, G. (2017). Boosting the energy renovation rate of the private building stock in Italy: Policies and innovative GIS-based tools. Sustainable Cities and Society, 34(July), 394–404. doi:10.1016/j.scs.2017.07.002.

[45] Azizi, E., Ahmadiahangar, R., Rosin, A., Martins, J., Lopes, R. A., Beheshti, M. T., & Bolouki, S. (2021). Residential energy flexibility characterization using non-intrusive load monitoring. Sustainable Cities and Society, 75(May), 103321. doi:10.1016/j.scs.2021.103321.

[46] Li, X., Luo, J., Li, Y., Wang, W., Hong, W., Liu, M., Li, X., & Lv, Z. (2022). Application of effective water-energy management based on digital twins technology in sustainable cities construction. Sustainable Cities and Society, 87(October), 104241. doi:10.1016/j.scs.2022.104241.

[47] Surroop, D., Raghoo, P., Wolf, F., Shah, K. U., & Jeetah, P. (2018). Energy access in Small Island Developing States: Status, barriers and policy measures. Environmental Development, 27, 58–69. doi:10.1016/j.envdev.2018.07.003.

[48] Trinh, H. A., Truong, H. V. A., Do, T. C., Nguyen, M. H., Phan, V. Du, & Ahn, K. K. (2022). Optimization-based energy management strategies for hybrid construction machinery: A review. Energy Reports, 8, 6035–6057. doi:10.1016/j.egyr.2022.04.050.

[49] Żuk, P. (2023). Soft power and the media management of energy transition: Analysis of the media narrative about the construction of nuclear power plants in Poland. Energy Reports, 9, 568–583. doi:10.1016/j.egyr.2022.11.192.

[50] Paulu, A., Vitvarová, M., & Kočí, V. (2022). Quantifying the industry-wide symbiotic potential: LCA of construction and energy waste management in the Czech Republic. Sustainable Production and Consumption, 34, 55–64. doi:10.1016/j.spc.2022.08.033.

[51] Olawumi, T. O., Chan, D. W. M., Wong, J. K. W., & Chan, A. P. C. (2018). Barriers to the integration of BIM and sustainability practices in construction projects: A Delphi survey of international experts. Journal of Building Engineering, 20, 60–71. doi:10.1016/j.jobe.2018.06.017.

[52] Che Ibrahim, C. K. I., Manu, P., Belayutham, S., Mahamadu, A. M., & Antwi-Afari, M. F. (2022). Design for safety (DfS) practice in construction engineering and management research: A review of current trends and future directions. Journal of Building Engineering, 52, 104352. doi:10.1016/j.jobe.2022.104352.

[53] Ikudayisi, A. E., Chan, A. P. C., Darko, A., & Adedeji, Y. M. D. (2023). Integrated practices in the Architecture, Engineering, and Construction industry: Current scope and pathway towards Industry 5.0. Journal of Building Engineering, 73(May), 106788. doi:10.1016/j.jobe.2023.106788.

[54] Tafesse, S., Girma, Y. E., & Dessalegn, E. (2022). Analysis of the socio-economic and environmental impacts of construction waste and management practices. Heliyon, 8(3), 9169. doi:10.1016/j.heliyon.2022.e09169.

[55] Jia, J. J., Xu, J. H., Fan, Y., & Ji, Q. (2018). Willingness to accept energy-saving measures and adoption barriers in the residential sector: An empirical analysis in Beijing, China. Renewable and Sustainable Energy Reviews, 95, 56–73. doi:10.1016/j.rser.2018.07.015.

[56] Ali, A. H., El-Mahdy, G. M., Ibrahim, A. H., & Daoud, A. O. (2023). Towards the Adoption of Modular Construction in Residential Projects in Egypt: Benefits, Barriers, and Enablers. Towards a Sustainable Construction Industry: The Role of Innovation and Digitalisation, 1, 72–81. doi:10.1007/978-3-031-22434-8_8.

[57] Hassan Ali, A., Farouk Kineber, A., Elshaboury, N., Arashpour, M., & Osama Daoud, A. (2023). Analysing multifaceted barriers to modular construction in sustainable building projects: a comprehensive evaluation using multi-criteria decision making. International Journal of Construction Management, 0(0), 1–17. doi:10.1080/15623599.2023.2299557.

[58] Ali, A. H., Kineber, A. F., Elyamany, A., Hussein Ibrahim, A., & Daoud, A. O. (2023). Exploring stationary and major modular construction challenges in developing countries: a case study of Egypt. Journal of Engineering, Design and Technology, 1–30. doi:10.1108/JEDT-03-2023-0099.

[59] Somachandra, W. D. I. V., Sylva, K. K. K., Bandara, C. S., & Dissanayake, P. B. R. (2023). Corporate social responsibility (CSR) practices in the construction industry of Sri Lanka. International Journal of Construction Management, 23(13), 2230-2238. doi:10.1080/15623599.2022.2049489.

[60] Williams, K., & Dair, C. (2006). What is stopping sustainable building in England? Barriers experienced by stakeholders in delivering sustainable developments. Sustainable Development, 15(3), 135–147. Portico. doi:10.1002/sd.308.

[61] Iqbal, M., Ma, J., Ahmad, N., Hussain, K., & Usmani, M. S. (2021). Promoting sustainable construction through energy-efficient technologies: an analysis of promotional strategies using interpretive structural modeling. International Journal of Environmental Science and Technology, 18(11), 3479–3502. doi:10.1007/s13762-020-03082-4.

[62] Sarkar, A., Qian, L., Peau, A. K., & Shahriar, S. (2021). Modeling drivers for successful adoption of green business: an interpretive structural modeling approach. Environmental Science and Pollution Research, 28(1), 1077–1096. doi:10.1007/s11356-020-10490-z.

[63] Shahzad, U. (2020). Environmental taxes, energy consumption, and environmental quality: Theoretical survey with policy implications. Environmental Science and Pollution Research, 27(20), 24848–24862. doi:10.1007/s11356-020-08349-4.

[64] Van Gorp, J. C. (2004). Maximizing energy savings with energy management systems. Strategic Planning for Energy and the Environment, 24(3), 57–69. doi:10.1080/10485230409509667.

[65] Li, B., Akintoye, A., Edwards, P. J., & Hardcastle, C. (2005). Critical success factors for PPP/PFI projects in the UK construction industry. Construction Management and Economics, 23(5), 459–471. doi:10.1080/01446190500041537.

[66] Serpell, A., Kort, J., & Vera, S. (2013). Awareness, actions, drivers and barriers of sustainable construction in Chile. Technological and Economic Development of Economy, 19(2), 272–288. doi:10.3846/20294913.2013.798597.

[67] Love, P. E. D., Niedzweicki, M., Bullen, P. A., & Edwards, D. J. (2012). Achieving the Green Building Council of Australia's World Leadership Rating in an Office Building in Perth. Journal of Construction Engineering and Management, 138(5), 652–660. doi:10.1061/(asce)co.1943-7862.0000461.

[68] Shan, M., Liu, W. Q., Hwang, B. G., & Lye, J. M. (2020). Critical success factors for small contractors to conduct green building construction projects in Singapore: identification and comparison with large contractors. Environmental Science and Pollution Research, 27(8), 8310–8322. doi:10.1007/s11356-019-06646-1.

[69] Bruno, S., Dellino, G., La Scala, M., & Meloni, C. (2019). A microforecasting module for energy management in residential and tertiary buildings. Energies, 12(6). doi:10.3390/en12061006.

[70] Laskurain, I., Ibarloza, A., Larrea, A., & Allur, E. (2017). Contribution to energy management of the main standards for environmental management systems: The case of ISO 14001 and EMAS. Energies, 10(11). doi:10.3390/en10111758.

[71] Lipu, M. S. H. (2013). An Approach towards Sustainable Energy Performance by Green Building: A Review of Current Features, Benefits and Barriers. International Journal of Renewable and Sustainable Energy, 2(4), 180. doi:10.11648/j.ijrse.20130204.18.

[72] Bhavsar, V., Sridharan, S. R., & Sudarsan, J. S. (2023). Barriers to circular economy practices during construction and demolition waste management in an emerging economy. Resources, Conservation and Recycling Advances, 20(November), 200198. doi:10.1016/j.rcradv.2023.200198.

[73] Tan, T., Chen, K., Xue, F., & Lu, W. (2019). Barriers to Building Information Modeling (BIM) implementation in China's prefabricated construction: An interpretive structural modeling (ISM) approach. Journal of Cleaner Production, 219, 949-959. doi:10.1016/j.jclepro.2019.02.141.

[74] Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2015). Purposeful Sampling for Qualitative Data Collection and Analysis in Mixed Method Implementation Research. Administration and Policy in Mental Health and Mental Health Services Research, 42(5), 533–544. doi:10.1007/s10488-013-0528-y.

[75] Wong, K. K. K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. Marketing bulletin, 24(1), 1-32.

[76] Talafubieke, M., Mai, S., & Xialifuhan, N. (2021). Evaluation of the Virtual Economic Effect of Tourism Product Emotional Marketing Based on Virtual Reality. Frontiers in Psychology, 12. doi:10.3389/fpsyg.2021.759268.

[77] Roberts, N., Thatcher, J. B., & Grover, V. (2010). Advancing operations management theory using exploratory structural equation modelling techniques. International Journal of Production Research, 48(15), 4329–4353. doi:10.1080/00207540902991682.

[78] Singh, A. K., Kumar, V. R. P., Shoaib, M., Adebayo, T. S., & Irfan, M. (2023). A strategic roadmap to overcome blockchain technology barriers for sustainable construction: A deep learning-based dual-stage SEM-ANN approach. Technological Forecasting and Social Change, 194, 122716. doi:10.1016/j.techfore.2023.122716.

[79] Kineber, A. F., Singh, A. K., Fazeli, A., Mohandes, S. R., Cheung, C., Arashpour, M., Ejohwomu, O., & Zayed, T. (2023). Modelling the relationship between digital twins implementation barriers and sustainability pillars: Insights from building and construction sector. Sustainable Cities and Society, 99, 104930. doi:10.1016/j.scs.2023.104930.

[80] Ali, A. H., Kineber, A. F., Elyamany, A., Ibrahim, A. H., & Daoud, A. O. (2023). Identifying and assessing modular construction implementation barriers in developing nations for sustainable building development. Sustainable Development, 31(5), 3346–3364. doi:10.1002/sd.2589.

[81] Ali, A. H., Elyamany, A., Ibrahim, A. H., Kineber, A. F., & Daoud, A. O. (2023). Modelling the relationship between modular construction adoption and critical success factors for residential projects in developing countries. International Journal of Construction Management, 1–12. doi:10.1080/15623599.2023.2185940.

[82] Kineber, A. F., Oke, A., Hamed, M. M., Alyanbaawi, A., Elmansoury, A., & Daoud, A. O. (2023). Decision Making Model for Identifying the Cyber Technology Implementation Benefits for Sustainable Residential Building: A Mathematical PLS-SEM Approach. Sustainability (Switzerland), 15(3), 2458. doi:10.3390/su15032458.

[83] Bello, A. O., Eje, D. O., Idris, A., Semiu, M. A., & Khan, A. A. (2023). Drivers for the implementation of modular construction systems in the AEC industry of developing countries. Journal of Engineering, Design and Technology, 2018. doi:10.1108/JEDT-11-2022-0571.

[84] Nureen, N., Xin, Y., Irfan, M., & Fahad, S. (2023). Going green: how do green supply chain management and green training influence firm performance? Evidence from a developing country. Environmental Science and Pollution Research, 30(20), 57448–57459. doi:10.1007/s11356-023-26609-x.

[85] Waqar, A., Othman, I., & Pomares, J. C. (2023). Impact of 3D Printing on the Overall Project Success of Residential Construction Projects Using Structural Equation Modelling. International Journal of Environmental Research and Public Health, 20(5), 3800. doi:10.3390/ijerph20053800.

[86] Khan, S. A., Mubarik, M. S., Kusi-Sarpong, S., Gupta, H., Zaman, S. I., & Mubarik, M. (2022). Blockchain technologies as enablers of supply chain mapping for sustainable supply chains. Business Strategy and the Environment, 31(8), 3742–3756. doi:10.1002/bse.3029.

[87] Oke, A. E., Farouk Kineber, A., Abdel-Tawab, M., Abubakar, A. S., Albukhari, I., & Kingsley, C. (2023). Barriers to the implementation of cloud computing for sustainable construction in a developing economy. International Journal of Building Pathology and Adaptation, 41(5), 988–1013. doi:10.1108/IJBPA-07-2021-0098.

[88] Rajbhandari, S., Devkota, N., Khanal, G., Mahato, S., & Paudel, U. R. (2022). Assessing the industrial readiness for adoption of industry 4.0 in Nepal: A structural equation model analysis. Heliyon, 8(2), 8919. doi:10.1016/j.heliyon.2022.e08919.

[89] Garg, R. K. (2021). Structural equation modeling of E-supplier selection criteria in mechanical manufacturing industries. Journal of Cleaner Production, 311(May), 127597. doi:10.1016/j.jclepro.2021.127597.

[90] Teng, J., Mu, X., Wang, W., Xu, C., & Liu, W. (2019). Strategies for sustainable development of green buildings. Sustainable Cities and Society, 44, 215–226. doi:10.1016/j.scs.2018.09.038.

[91] Gunduz, M., Birgonul, M. T., & Ozdemir, M. (2017). Fuzzy Structural Equation Model to Assess Construction Site Safety Performance. Journal of Construction Engineering and Management, 143(4), 4016112. doi:10.1061/(asce)co.1943-7862.0001259.

[92] Podsakoff, P. M., & Organ, D. W. (1986). Self-Reports in Organizational Research: Problems and Prospects. Journal of Management, 12(4), 531–544. doi:10.1177/014920638601200408.

[93] MacKenzie, S. B., & Podsakoff, P. M. (2012). Common Method Bias in Marketing: Causes, Mechanisms, and Procedural Remedies. Journal of Retailing, 88(4), 542–555. doi:10.1016/j.jretai.2012.08.001.

[94] Durdyev, S., Ismail, S., Ihtiyar, A., Abu Bakar, N. F. S., & Darko, A. (2018). A partial least squares structural equation modeling (PLS-SEM) of barriers to sustainable construction in Malaysia. Journal of Cleaner Production, 204, 564–572. doi:10.1016/j.jclepro.2018.08.304.

[95] Munianday, P., Radzi, A. R., Esa, M., & Rahman, R. A. (2022). Optimal Strategies for Improving Organizational BIM Capabilities: PLS-SEM Approach. Journal of Management in Engineering, 38(3). doi:10.1061/(asce)me.1943-5479.0001038.

[96] Ali, A. H., Kineber, A. F., Elyamany, A., Ibrahim, A. H., & Daoud, A. O. (2023). Modelling the role of modular construction's critical success factors in the overall sustainable success of Egyptian housing projects. Journal of Building Engineering, 71(April), 1–18,. doi:10.1016/j.jobe.2023.106467.

[97] Abdel-Tawab, M., Kineber, A. F., Chileshe, N., Abanda, H., Ali, A. H., & Almukhtar, A. (2023). Building Information Modelling Implementation Model for Sustainable Building Projects in Developing Countries: A PLS-SEM Approach. Sustainability (Switzerland), 15(12), 1–21. doi:10.3390/su15129242.

[98] Awang, Z., Wan Afthanorhan, W. M. A., & Asri, M. A. M. (2015). Parametric and Non-Parametric Approach in Structural Equation Modeling (SEM): The Application of Bootstrapping. Modern Applied Science, 9(9), 58–67. doi:10.5539/mas.v9n9p58.

[99] Li, C., Zhang, Y., & Xu, Y. (2022). Factors Influencing the Adoption of Blockchain in the Construction Industry: A Hybrid Approach Using PLS-SEM and fsQCA. Buildings, 12(9). doi:10.3390/buildings12091349.

[100] Ashaari, M. A., Singh, K. S. D., Abbasi, G. A., Amran, A., & Liebana-Cabanillas, F. J. (2021). Big data analytics capability for improved performance of higher education institutions in the Era of IR 4.0: A multi-analytical SEM & ANN perspective. Technological Forecasting and Social Change, 173, 121119. doi:10.1016/j.techfore.2021.121119.

[101] Lo, P. S., Dwivedi, Y. K., Wei-Han Tan, G., Ooi, K. B., Cheng-Xi Aw, E., & Metri, B. (2022). Why do consumers buy impulsively during live streaming? A deep learning-based dual-stage SEM-ANN analysis. Journal of Business Research, 147, 325–337. doi:10.1016/j.jbusres.2022.04.013.

[102] Wong, L. W., Leong, L. Y., Hew, J. J., Tan, G. W. H., & Ooi, K. B. (2020). Time to seize the digital evolution: Adoption of blockchain in operations and supply chain management among Malaysian SMEs. International Journal of Information Management, 52, 101997. doi:10.1016/j.ijinfomgt.2019.08.005.

[103] Leong, L. Y., Hew, T. S., Ooi, K. B., & Wei, J. (2020). Predicting mobile wallet resistance: A two-staged structural equation modeling-artificial neural network approach. International Journal of Information Management, 51(November), 102047. doi:10.1016/j.ijinfomgt.2019.102047.

[104] Nicolas, C., Kim, J., & Chi, S. (2020). Quantifying the dynamic effects of smart city development enablers using structural equation modeling. Sustainable Cities and Society, 53, 101916. doi:10.1016/j.scs.2019.101916.

[105] Tawalare, A., Laishram, B., & Thottathil, F. (2020). Relational Partnership in Public Construction Organizations: Front-Line Employee Perspective. Journal of Construction Engineering and Management, 146(1), 04019086. doi:10.1061/(asce)co.1943-7862.0001723.

[106] Kar, S., & Jha, K. N. (2021). Exploring the Critical Barriers to and Enablers of Sustainable Material Management Practices in the Construction Industry. Journal of Construction Engineering and Management, 147(9), 04021102. doi:10.1061/(asce)co.1943-7862.0002125.

[107] Chen, Y., Dib, H., Cox, R. F., Shaurette, M., & Vorvoreanu, M. (2016). Structural Equation Model of Building Information Modeling Maturity. Journal of Construction Engineering and Management, 142(9), 4016032. doi:10.1061/(asce)co.1943-7862.0001147.

[108] Kursunoglu, N., Onder, S., & Onder, M. (2022). The Evaluation of Personal Protective Equipment Usage Habit of Mining Employees Using Structural Equation Modeling. Safety and Health at Work, 13(2), 180–186. doi:10.1016/j.shaw.2022.03.004.

[109] Nwaogu, J. M., Chan, A. P. C., & Naslund, J. A. (2022). Measures to Improve the Mental Health of Construction Personnel Based on Expert Opinions. Journal of Management in Engineering, 38(4), 1–17. doi:10.1061/(asce)me.1943-5479.0001045.

[110] Cruz-Jesus, F., Pinheiro, A., & Oliveira, T. (2019). Understanding CRM adoption stages: empirical analysis building on the TOE framework. Computers in Industry, 109, 1–13. doi:10.1016/j.compind.2019.03.007.

[111] Rouhanizadeh, B., & Kermanshachi, S. (2022). Investigation of the Causal Relationships among Different Barrier Categories to Timely Posthurricane Recovery. Natural Hazards Review, 23(3). doi:10.1061/(asce)nh.1527-6996.0000565.

[112] Arpaci, I., Karatas, K., Kusci, I., & Al-Emran, M. (2022). Understanding the social sustainability of the Metaverse by integrating UTAUT2 and big five personality traits: A hybrid SEM-ANN approach. Technology in Society, 71, 102120. doi:10.1016/j.techsoc.2022.102120.

[113] Wang, G., Tan, G. W. H., Yuan, Y., Ooi, K. B., & Dwivedi, Y. K. (2022). Revisiting TAM2 in behavioral targeting advertising: A deep learning-based dual-stage SEM-ANN analysis. Technological Forecasting and Social Change, 175, 121345. doi:10.1016/j.techfore.2021.121345.

[114] Prasad Das, C., Kumar Swain, B., Goswami, S., & Das, M. (2021). Prediction of traffic noise induced annoyance: A two-staged SEM-Artificial Neural Network approach. Transportation Research Part D: Transport and Environment, 100(September), 103055. doi:10.1016/j.trd.2021.103055.

[115] Loh, X. M., Lee, V. H., & Leong, L. Y. (2022). Mobile-lizing continuance intention with the mobile expectation-confirmation model: An SEM-ANN-NCA approach. Expert Systems with Applications, 205, 117659. doi:10.1016/j.eswa.2022.117659.

[116] Elseufy, S. M., Hussein, A., & Badawy, M. (2022). A hybrid SEM-ANN model for predicting overall rework impact on the performance of bridge construction projects. Structures, 46(June), 713–724. doi:10.1016/j.istruc.2022.10.100.