

# **Environmental Impact Assessment: A PLS-SEM Model Based on Empirical Community Perceptions**

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## **Abstract**

Environmental Impact Assessment (EIA) is the primary technical and administrative instrument for decision-making on projects, activities, and environmental aspects that may generate significant effects on the natural and social environment. In infrastructure projects, the EIA is a prerequisite for initiating construction and operational phases. This article analyzes the relationships between project activities, resulting environmental aspects, and impact assessment using Structural Equation Modeling PLS-SEM. While the conceptual model builds on the factors proposed by Conesa (2009), a distinct methodological approach was adopted, moving beyond traditional qualitative evaluation. A Likert-scale questionnaire was administered to residents of the study area, who assessed the extent to which specific project activities are associated with environmental impacts. Unlike ex ante approaches based on expert judgment and predictive models, this study incorporates an ex-post evaluation, integrating empirical data and the lived experiences of affected communities. This shift aligns with the principles of Participatory Action Research (PAR), emphasizing co-construction of knowledge and active stakeholder engagement. The findings highlight how specific construction activities influence environmental impacts, offering valuable insights for regional planning in Coahuila. The proposed methodological framework can be applied to similar contexts, particularly where PAR-based strategies can be integrated to strengthen transparency, accountability, and collective learning in environmental management.

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## 1. Introduction

Environmental Impact Assessment is the main technical and administrative tool for decision-making related to projects, activities, and environmental aspects that have the potential to generate significant impacts on the natural and social environment. In the case of infrastructure projects, the EIA is an essential requirement that conditions the start of construction and operation phases. However, in some contexts, a formal environmental license is not explicitly required; instead, a technical report or environmental statement is used to demonstrate the project's environmental viability (Dendena & Corsi, 2015; Enshassi et al., 2014; Morgan, 2012; Martínez, 2010; Nita et al., 2022). This article analyzes the relationships between project components (F1), the resulting environmental aspects (F2), and the assessment of environmental impacts (F3), using a structural equation modeling approach through the PLS-SEM technique. While the conceptual model is based on the factors proposed by Conesa (2009), a different methodological approach was adopted, departing from the traditional qualitative evaluation. Instead of relying solely on expert assessments, a Likert-Scale questionnaire was applied to residents of the study area, asking them to rate to what extent certain project-related activities or conditions are associated with relevant environmental impacts.

The variables considered include water consumption (Otterpohl et al., 1997), soil management (Lal, 2000), waste management, transportation of materials (Shakantu et al., 2003), use of heavy machinery (Shehadeh et al., 2022), excessive consumption of resources, air disturbance (Zhang et al., 2013), generation of hazardous waste, release of particles (Wang et al., 2020), use of chemicals, air quality deterioration (Tétreault, 2016), depletion of water resources, air pollution (Zaman et al., 2016), contribution to climate change, and soil contamination (Otterpohl et al., 1997; Lal, 2000, Shakantu et al., 2003).

This participatory strategy gave voice to those who directly experienced the consequences of these projects, enriching the evaluation process by incorporating empirical evidence from the context using the Participatory Action Research (PAR) model (Goebel et al., 2019). While not all respondents have specialized technical training, their everyday experiences provide localized knowledge often missing from official reports.

Finally, a series of recommendations are proposed to strengthen the environmental impact assessment process in the region under study, aiming to promote greater objectivity, traceability, and usefulness for sustainable decision-making.

The integration of Environmental Impact Assessment into decision-making processes can follow three main approaches (Fischer, 2010):

- **Reactive:** This occurs when a project, not previously included in any plan, is subjected to environmental evaluation only after the decision to implement it has already been made. This method is undesirable, as it has limited effectiveness due to its post-decision timing.
- **Semi-adaptive:** In this case, the EIA is conducted before making a final decision (approval, modification, or rejection) on a project that was not part of a prior plan. This approach represents a significant improvement over the reactive model and is currently the most common practice in Spain.

**Adaptive:** This is the most suitable approach, where all projects are embedded within a pre-existing plan. The EIA benefits from the information provided by the plan, allowing it to focus on the most critical or contentious aspects. Environmental protection is further strengthened if the plan itself has undergone a Strategic Environmental Assessment (SEA).

## **2. Preliminary Notes**

Construction activities have a direct and significant impact on the environment, particularly using heavy machinery, material transportation, and land disturbance. These processes contribute to air and noise pollution, resource depletion, ecosystem degradation, and greenhouse gas emissions. Although mitigation strategies such as responsible construction practices and Environmental Impact Assessments exist, their implementation remains challenging due to limited enforcement, technical complexity, and cost considerations. Li et al. (2010) using a Life-Cycle Assessment (LCA) approach in the U.S., classified environmental impacts into three main categories: ecosystems (65%), community health (27%), and natural resource depletion (8%). In Malaysia, Zolfagharian et al. (2012) reported similar trends, with ecosystem impacts dominating (67.5%), followed by impacts on natural resources (21%) and the community (11.5%). These results confirm that construction activities are primary drivers of environmental pressure across different national contexts, reinforcing their role as exogenous variables (F1) in structural models.

From a methodological perspective, identifying and evaluating construction-related actions as distinct indicators within predictive models allows for early detection of potential environmental risks. This enhances the ability of planning tools—such as PLS-SEM models—to simulate environmental outcomes before projects begin. It also supports the formulation of preventive strategies that incorporate both technical data and the perceptions of affected communities. The construction sector is a significant consumer of freshwater, accounting for nearly 20 % of total global water use within the built environment. Construction and operational water use can represent up to 35 % of a building's life-cycle environmental impact in water-stressed regions (Mannan & Al-Ghamdi, 2022). High water demand for tasks such as material mixing, dust control, and site cleaning places significant strain on local aquifers, especially in arid or semi-arid zones.

Construction activities often lead to soil compaction, erosion, nutrient loss, and

disruption of soil structure. Compaction reduces soil porosity, impairs water infiltration, and increases runoff, erosion, greenhouse gas emissions, and biodiversity loss (Kazaz et al., 2022). Effective soil management practices, including soil conservation and regeneration, are essential to mitigate these impacts and preserve ecosystem functions (Kucher et al., 2019). Construction generates substantial volumes of waste, often involving hazardous materials like paints, adhesives, and chemical residues. Globally, construction and demolition (C&D) waste contributes up to 40 % of total solid waste, with a large fraction currently sent to landfills where toxic leachate can contaminate soil and groundwater (Broujeni et al., 2016). Sustainable waste strategies—such as recycling, reuse, and circular economy approaches, are vital to reduce environmental harm and resource depletion.

## 2.1 Environmental Aspects

Environmental aspects refer to the components of the physical, biological, and perceptual environment that can be altered by construction activities. Within the PLS model framework, these aspects function as mediating variables between human actions (F1) and observable environmental impacts (F3). Their proper characterization enables a more precise identification of vulnerable areas that should be monitored or proactively managed.

The intensive consumption of natural resources is inherent to urbanization and economic expansion processes. As Sahui Maldonado (2014) points out, in line with Rostow's development theory, economic growth is often accompanied by an indiscriminate increase in the supply and demand for goods and services. This dynamic reflects a consumer society model, where the accelerated use of resources leaves a significant ecological footprint, particularly in sectors such as construction, which require large quantities of materials, water, energy, and chemical products to sustain their operations.

The management of waste, especially hazardous waste, has become a global challenge associated with the increasing complexity of production processes and the shortening of product life cycles. Martínez et al. (2005) warn that this phenomenon is linked to urban concentration, which intensifies pressure on local ecosystems. Decoupling economic growth from waste generation is an unresolved goal that demands alignment between development policies and sustainability criteria, especially in industries such as construction that produce high volumes of mixed and hazardous waste.

The construction industry significantly contributes to atmospheric degradation, both during and after project execution. Acevedo et al. (2012) emphasize that this activity emits large amounts of primary pollutants such as particulate matter, CO, NO<sub>2</sub>, CO<sub>2</sub>, and SO<sub>2</sub>, which may transform into more aggressive secondary pollutants like SO<sub>3</sub>, H<sub>2</sub>SO<sub>4</sub>, and NH<sub>3</sub>. These emissions not only alter air quality but also worsen the effects on human health and ecosystems, making rigorous monitoring essential from the early stages of construction projects.

## **2.2 Environmental Impact**

Environmental impact represents the tangible consequences of construction activities on natural systems. In the PLS-SEM model, this factor acts as an endogenous variable, integrating effects from project activities (F1) mediated by environmental sensitivities (F2). It encompasses five critical impact dimensions: air quality deterioration, depletion of water resources, air pollution, climate change contribution, and soil contamination. Air quality deterioration and air pollution arise from construction-related emissions of particulate matter (PM<sub>10</sub>, PM<sub>2.5</sub>), nitrogen dioxide (NO<sub>2</sub>), carbon monoxide (CO), sulfur dioxide (SO<sub>2</sub>) and volatile organic compounds.

These pollutants reduce air quality and pose serious health risks to workers and nearby communities. Notably, studies have shown that increased NO<sub>2</sub> levels directly associate with elevated accident rates on construction sites (Lavy et al., 2023). A global literature review confirms construction as a major industrial source of particulate emissions and urban pollution trends (Wieser et al., 2021).

Depletion of water resources results from high consumption for dust suppression, mixing and cleaning during construction. In arid or overexploited regions, construction amplifies pressure on aquifers. Research highlights accelerating groundwater decline across 71% of global aquifers (Scanlon et al., 2012), and urban extraction frequently exceeds recharge rates (Alao et al., 2024). Tunneling and large-scale excavation have especially detrimental long-term impacts (Behzad et al., 2022). Contribution to climate change emanates from lifecycle emissions, including fuel combustion for machinery and transport, and embodied carbon in cement-based materials. Construction and building sectors contribute between 25–40% of global CO<sub>2</sub> emissions, with roughly half linked to construction phases and concrete production (~4–8% worldwide).

Soil contamination occurs due to chemical spills, improper disposal of hazardous waste, and runoff carrying heavy metals or organic pollutants. Although case-specific research is less widespread, Preene and Brassington (2003) emphasize the need to monitor and evaluate groundwater and soil impacts arising from excavation and dewatering activities. Collectively, these five dimensions—air quality deterioration, air pollution, water depletion, greenhouse gas emissions, and soil contamination—highlight critical domains of environmental harm. Modeling them as indicators within the PLS-SEM framework allows for early detection of risk and supports evidence-based mitigation strategies grounded in both technical data and social perception.

Projects or activities group the specific actions carried out during the construction process of a building. Within the methodological framework proposed by Conesa (2009), these activities constitute the starting point for environmental impact analysis, as they represent human interventions that directly interact with the physical and social environment. The inclusion of these items in the PLS model responds to their causal role in the chain of environmental effects. Activities such as water consumption (CONAG) (Otterpohl et al., 1997), the use of heavy

machinery (USMAQ) (Shehadeh et al., 2022), or the transportation of materials (TRAMT) (Shakantu et al., 2003) are representative examples, since they produce immediate physical alterations in the environment; influence the magnitude and nature of the affected environmental aspects; and are controllable and quantifiable by the project.

From a structural perspective, these indicators should be considered exogenous (independent) variables that initiate the impact processes. Their proper identification allows for clear assignment of responsibility to the project developer and supports the anticipation of mitigation measures.

*H1: The higher the level of project activities, the greater the impact on environmental aspects.*

This second block represents the components of the physical, biological, and social environment that may be altered by the activities associated with construction projects. Conesa (2009) classifies them as “receptor elements” of the impact, since they do not generate effects by themselves but rather receive them because of human actions. In the PLS model, environmental aspects play an intermediate role, acting as mediating variables between project activities and observable impacts. The selected items, such as EMGAS, COEXC, and USSUQ (Zhang et al., 2013; Tétreault, 2016) are justified because they:

Represent specific elements of the environment that interact directly with construction processes.

- Allow for precise categorization by subsystem (physical, biotic, perceptual).
- Serve as indicators of environmental sensitivity to human disturbances.

From a methodological standpoint, this category is essential for identifying which components of the environment are most vulnerable and should be monitored or protected. Their correct modeling facilitates the design of targeted environmental management strategies, increasing the effectiveness of mitigation measures.

*H2: The greater the alteration of environmental aspects, the greater the environmental impact.*

This third factor, Environmental Impact, represents the actual or potential effects that project activities generate on environmental components. In Conesa’s (2009) methodological framework, environmental impact is not merely the outcome of the interaction but a quantifiable and qualitative expression of that relationship. The items included in the models such as CONCAM, COAIR, COSUE, and AGREH (Zaman et al., 2016; Otterpohl et al., 1997; Lal, 2000; Shakantu et al., 2003) clearly correspond to this category, as they:

- Reflect tangible alterations in physical environments and human health.
- Allow for a graded evaluation of damage in terms of intensity, extent, and duration.
- Facilitate the prioritization of corrective and preventive measures based on the level of risk.

From a methodological perspective, these indicators act as endogenous variables that receive the combined effect of project activities and the vulnerability of environmental aspects. Their proper identification in the PLS model is crucial for evaluating the effectiveness of mitigation policies and designing future scenarios. Moreover, their inclusion provides empirical validation of the model's causal relationships and offers a theoretical basis to assess the principle of sustainability, that is, human activities must be compatible with the preservation of the environment and public health.

*H3: The higher the level of project activities, the greater the environmental impact.*

Based on the three hypotheses, the conceptual framework developed by the authors considers three latent variable project activities (F1), environmental aspects (F2), and environmental impacts (F3)—and the hypotheses that define their relationships. The model is based on previous works by Conesa (2009) and Kineber & Hamed (2022).

### 3. Methodology

The Environmental Impact Assessment aims to anticipate the alterations that a given action may cause to the environment. Its main purpose is to analyze the environmental effects of projects, work, or activities before they are carried out. Through this assessment, the goal is to predict and evaluate the potential consequences on the surrounding environment. Additionally, the EIA helps identify corrective or mitigating measures. Although eliminating negative impacts is difficult, efforts are made to minimize them as much as possible. Based on the above, the objective of this study is to evaluate the environmental impact (F3) caused by the various activities that comprise a project (F1), as well as the different environmental aspects involved (F2) in the construction sector.

According to the National Statistical Directory of Economic Units, in 2022, the registered population under code 23 (construction) in the state of Coahuila consisted of 189 companies with between 11 and 250 employees (INEGI, 2022).

The development of measures for designing a research instrument or survey involves a series of structured steps to ensure its validity and reliability. The process began with a qualitative study involving a panel of experts, which included four business owners with backgrounds in architecture or civil engineering from northern Mexico, three sustainability-focused university professors, and three doctoral students specializing in environmental topics.

This expert group reviewed the topics proposed by Conesa (2009), which are organized into the categories of Projects or Activities, Environmental Aspects, and Environmental Impacts. From the initial list, the experts selected a total of 19 items for inclusion in the instrument.

- **Projects or Activities:** Water consumption, soil management, waste management, transportation of materials, and use of heavy machinery.
- **Environmental Aspects:** Excessive consumption of resources, air disturbance, generation of hazardous waste, release of particles, and use of chemicals.
- **Environmental Impacts:** Deterioration of air quality, depletion of water resources, air pollution, contribution to climate change, and soil contamination.

The research instrument, designed using Google Forms, was distributed through the institutional platform and shared via direct WhatsApp messages to facilitate access. The survey was conducted between August and October 2023 and targeted all companies in the sector, inviting owners and managers to evaluate 19 items related to environmental impact. A 5-point Likert scale was used, where 5 indicated “completely satisfied” and 1 “completely dissatisfied.” A total of 141 responses were collected, representing a response rate of 78.3%. The dissemination and outreach efforts were supported by students and graduates of the Doctorate in Administration and High Management (DAAD), most of whom are civil engineers or architects, as well as by the Civil Engineers Association of Saltillo A.C. and the Architects Association of the Comarca Lagunera A.C.

An additional and key element was the active participation of residents or those who have previously experienced similar situations, allowing their direct experiences to be incorporated into the environmental assessment. Participatory Action Research (PAR) is a methodological approach that combines knowledge generation with social transformation. Unlike traditional methods, PAR recognizes participants not as objects of study but as active subjects who co-construct the research process (Kemmis et al., 2014).

In this study, while the application of the PLS-SEM model focuses on the technical evaluation of environmental impacts, the inclusion of citizen perceptions through surveys represents an initial step toward a participatory logic. However, to advance toward a true PAR framework, it is necessary to incorporate mechanisms that allow affected communities to engage in the design, interpretation, and application of the results.

Applied to the context of environmental assessment, this approach would enable communities not only to respond to surveys but also to:

- Participate in defining relevant environmental indicators.
- Interpret the PLS model results collectively.
- Propose mitigation measures based on their situated knowledge.



PAR not only complements the technical model but transforms it into a tool for environmental justice. By integrating the voices of those who experience the impact noise, dust, air disturbance, landscape loss, the legitimacy of the assessment process is strengthened, and a more inclusive environmental governance is promoted.

The outer loadings and *p*-values were obtained through PLS-SEM analysis using SmartPLS 4. Only items with acceptable levels of reliability and statistical significance ( $p < 0.05$ ) were retained in the final measurement model. The item AFAIR (“Deterioration of air quality”) was removed as its factor loading was below 0.70, which improved the model’s reliability and validity indicators (see Table 1).

**Table 1: Constructs, items and conceptual definition of the items**

Constructs	Items	Final Questionnaire Item	Outer loading	<i>p</i> value
F1 Project or Activities	CONAG	Water consumption	0.793	0.000
	EMPOLV	Soil management	0.836	0.000
	MANRE	Waste management	0.787	0.000
	TRAMT	Transportation of materials	0.82	0.000
	USMAQ	Use of heavy machinery	0.817	0.000
F2 Environmental Aspects	COEXC	Excessive consumption of resources	0.852	0.000
	EMGAS	Air disturbance	0.75	0.000
	GEREP	Generation of hazardous waste	0.86	0.000
	LIPAR	Release of particles	0.764	0.000
	USSUQ	Use of chemicals	0.746	0.000
F3 Environmental Impacts	AFAIR	Deterioration of air quality	0.399	0.001
	AGREH	Depletion of water resources	0.874	0.000
	COAIR	Air pollution	0.729	0.000
	CONCAM	Contribution to climate change	0.89	0.000
	COSUE	Soil contamination	0.824	0.000

### 3.1 Reliability and Validity of the Measurement Scales

Table 2 shows that all values of Composite Reliability and Dijkstra-Henseler’s rho exceed the 0.7 threshold, thus establishing the reliability of the measures (Hair et al., 2017). To assess convergent validity, evaluations were based on the average variance extracted (AVE) index and outer loadings (Hair et al., 2017). The IVE for each construct exceeds the minimum threshold of 0.5, while the outer loading of each measurement item is above 0.7 Loh et al. (2022); therefore, the validity of the results is confirmed.

**Table 2: Construct Reliability and Validity**

Construct	Cronbach' alpha	Dijkstra-Henseler rho	CRI	AVE
F1 Project or activities	0.87	0.872	0.905	0.657
F2 Environmental aspect	0.854	0.861	0.896	0.634
F3 Environmental impact	0.852	0.857	0.901	0.696

The test of extracted variance developed by Fornell and Larcker (1981), (table 3) states that the shared variance between each pair of constructs should be lower than the average variance extracted (AVE) of each construct. Based on the results obtained, both tests provide sufficient evidence of discriminant validity (Hair et al., 2017).

**Table 3: Discriminant Validity (Fornell-Larcker Criterion)**

Construct	F1	F2	F3
F1 Project or activities	0.811		
F2 Environmental aspect	0.782	0.796	
F3 Environmental impact	0.76	0.714	0.834

The HTMT (Heterotrait-Monotrait Ratio) method is a robust alternative for assessing discriminant validity among constructs. According to Henseler et al. (2015), HTMT values should be below 0.85 (strict criterion) or 0.90 (more lenient criterion) to confirm discriminant validity. In Table 4, all values fall below these thresholds, providing additional evidence of discriminant validity among the analyzed constructs.

**Table 4: Discriminant Validity (Heterotrait-Monotrait Ratio HTMT)**

Constructs	F1	F2
F1 Project or activities		
F2 Environmental aspect	0.888	
F3 Environmental impact	0.881	0.827

## 4. Main Results

To assess the three hypotheses proposed in the conceptual model, the multivariate statistical technique of structural equation modeling using partial least squares (PLS-SEM) was applied with the statistical software SmartPLS 4 (Ringle et al., 2022). This method focuses on predicting a specific set of hypothetical relationships that maximize the explained variance in the dependent variables. It emphasizes prediction over explanation, which makes it particularly useful for exploratory studies, complex models with multiple simultaneous relationships, and research with moderately sized samples, Table 5.

**Table 5: Effect of projects and environmental aspects on environmental impact assessment**

Hypothesis	( $\beta$ ) path coef.	Standard deviation	Confidence Interval 95%	Effect Size $f^2$	T Statistics	p value	Hypothesis
PR-ACT $\rightarrow$ EN-ASP (H1)	0.782	0.038	(0.701 - 0.852)	1.569	3.661	0.000 ***	supported
EN-ASP $\rightarrow$ ENV-IM (H2)	0.309	0.097	(0.331 - 0.685)	0.272	3.146	0.000***	supported
PR-ACT $\rightarrow$ ENV-IM (H3)	0.519	0.089	(0.118 - 0.500)	0.116	2.372	0.018 **	supported

#### 4.1 Hypothesis Testing and Predictive Analysis

Hypothesis H1 (F1: project activities – F2: environmental aspects) shows the strongest results, with a t-value of 3.661, a p-value of 0.000, and a high  $\beta$  path coefficient. Hypothesis H2 (environmental aspects – F3: environmental impact assessment) is also supported. Hypothesis H3 (project activities – F3: environmental impact assessment) is accepted as well, based on adequate t-values and p-values.

The analysis of the predictive relevance using the  $f^2$  statistic indicates that values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively (Cohen, 1988). Hypothesis H1 exhibits a large predictive effect, H2 shows a medium effect, and H3 a small effect.

Table 6 presents the results for the endogenous constructs F2 (environmental aspects) and F3 (environmental impact). The  $R^2$  value ranges from 0 to 1, with higher values indicating greater predictive accuracy. It is difficult to establish general thresholds for acceptable  $R^2$  values, as they depend on the complexity of the model. Nonetheless,  $R^2$  values of 0.75, 0.50, and 0.25 are commonly interpreted as substantial, moderate, and weak, respectively (Hair et al., 2013; Henseler & Fassott, 2010). In this case, the coefficients of determination are considered moderate.

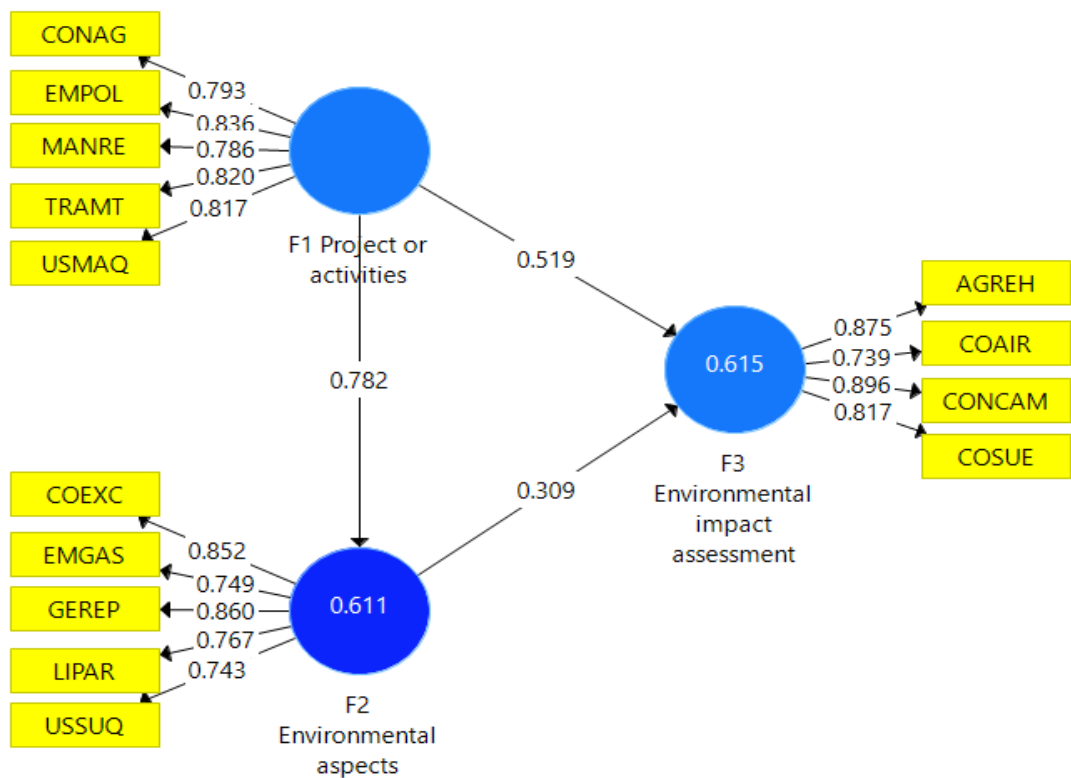
**Table 6: Endogenous Constructs**

Endogenous Constructs	Adjusted $R^2$	Confidence Interval (2.5% – 97.5%)	$Q^2$
F2 Environmental aspect (EN-ASP)	0.611	(0.331) - (0.685)	0.372
F3 Environmental impact (ENV-IM)	0.615	(0.118) - (0.500)	0.415

$R^2$  – Coefficient of Determination shows the percentage of variance in the dependent variable that is explained by the independent variables (Hair et al., 2019). In this study,  $R^2 = 0.611$  (F2) explains 61% of project or activities (F1);  $R^2 = 0.615$  (F3), environmental impact explains 61.5% of F1 and F2. Assessing Stone-Geisser's  $Q^2$  is crucial to examine the model's predictive capacity. It indicates

whether the indicators of a reflective endogenous construct can be reliably forecasted based on the exogenous variables (Falk & Miller, 1992).  $Q^2$  values of 0.02, 0.15, and 0.35 represent low, moderate, and high predictive relevance, respectively (Ringle et al., 2022).

SRMR (Standardized Root Mean Square Residual) values below the threshold of 0.08 indicate acceptable model fit (Hair et al., 2019). dULS (Unweighted Least Squares Discrepancy) and GD (Geodesic Discrepancy) were all calculated using 5,000 bootstrap subsamples, and all were below the HI99 threshold (99th percentile), indicating that the theoretical model fits the data well (RunZe et al., 2024; Maldonado et al., 2024; Molina et al., 2024).



**Figure 1: Results achieved within the framework of the conceptual model**

Source: Prepared by the authors based on the results of PLS-SEM

## 5. Conclusion

One of the main advantages of the PLS (Partial Least Squares) model is its predictive nature, in contrast to confirmatory models such as EQS. This allows for the estimation—based on participants' responses—that if timely corrective measures are not implemented, construction processes could contribute more severely to climate change. Assessing environmental impact after the damage has already occurred may provide useful lessons, but it does not prevent degradation. Given that construction activity continues to increase in the study area, it is essential to listen to these stakeholders to incorporate preventive measures with a sustainability-oriented approach.

Environmental impact assessments often rely on economic indices to quantify certain social costs and benefits. However, many significant effects on established social structures and natural resources resist accurate expression in monetary terms. The environmental impact assessment domain encompasses a broad array of environmental characteristic changes, some of which can be translated into economic indices. Indeed, several quantitative methods have been proposed to express and evaluate these impacts (Knights et al., 2013). Yet, impacts must be assessed promptly—not only to avoid unintended negative consequences but also to mitigate or attenuate those impacts that are unavoidable (Sandford, 1971).

Soil related impacts deserve particular attention. Soil loss or contamination, morphological changes, and induced risks such as landslides, flooding, erosion, or impeded transit are common consequences of earthmoving activities. Such activities often cause irreversible changes that affect both surface and groundwater. Reported impacts include physical water contamination by sediment, alterations in pH, terrestrial and aquatic biota degradation, shifts in fluvial dynamics, increased sediment load, salinization, eutrophication, and aquifer depression (Sentís, 2011). Similarly, road and pathway construction—and subsequent vehicular traffic—modifies air quality, producing dust, noise, air waves, vibrations, and toxic gases (Goodrum et al., 2009). Deforestation may also lead to microclimatic changes. All these effects can alter human health, flora, and fauna. Removal of plant or animal species and changes in land use may degrade ecosystems to irreversible states—especially with loss of soil cover. Modifying terrain morphology or vegetation can also alter landscapes, depending on factors such as fragility, visual quality, and exposure (Yetemen et al., 2010).

A comparative analysis with the model proposed by Kineber and Hamed (2022) reveals both conceptual and methodological complementarities. While their study focuses on identifying barriers to sustainability implementation in residential construction projects in Ghana, our model aims to evaluate environmental impacts through a participatory and empirical approach.

Their framework categorizes barriers into evaluation (E1–E8), preparation (P1–P7), and use (U1–U6), using PLS-SEM to assess structural relationships. In contrast, our model is structured around three latent variable project activities (F1), environmental aspects (F2), and environmental impacts (F3)—and integrates

community perceptions through Likert-scale surveys.

Both models employ PLS-SEM but differ in scope and application. The integration of our participatory approach could enhance the legitimacy and contextual relevance of sustainability measurements, while the barrier-focused structure of Kineber and Hamed (2022) offers a valuable lens to identify systemic challenges in environmental governance.

This comparison suggests that future research could benefit from hybrid models that combine impact evaluation with barrier identification, fostering more holistic and inclusive strategies for sustainable construction.

Comparative analysis reveals that the proposed model offers a more context-sensitive approach by incorporating participatory design and focusing on causal latent variables. This methodological choice enables a nuanced understanding of how specific construction activities influence environmental impacts, which is particularly relevant for regional planning in Coahuila. In contrast, the model by Kineber and Hamed (2022), while robust in identifying structural barriers, adopts a more generalized clustering strategy that may overlook localized dynamics.

The integration of community perspectives in the present study not only enhances the validity of the findings but also aligns with contemporary calls for inclusive and sustainable development practices. These distinctions suggest that methodological flexibility—especially in the application of PLS-SEM—can significantly enrich the relevance and applicability of research outcomes across diverse socio-environmental contexts.

The incorporation of an ex post assessment through the PLS-SEM framework afforded a refined understanding of the realized environmental impacts following project implementation. Anchored in empirical data and strengthened by participatory action research, this design integrated community perspectives frequently neglected in conventional ex ante analyses. Findings underscore citizen participation as foundational to environmental accountability. Future research should articulate comparative frameworks that align ex ante with ex post assessments, promoting more adaptive and transparent decision-making in construction and infrastructure planning.

## References

- [1] Conesa V. (2009). Guía metodológica para la evaluación del impacto ambiental. Mundi-Prensa Libros.
- [2] Dendena, B., & Corsi, S. (2015). The environmental and social impact assessment: A further step towards an integrated assessment process. *Journal of Cleaner Production*, 108, 965-977.  
<https://doi.org/10.1016/j.jclepro.2015.07.110>
- [3] Enshassi, A., Kochendoerfer, B., & Rizq, E. (2014). An evaluation of environmental impacts of construction projects. *Revista Ingeniería de Construcción*, 29(3), 234-254.  
<https://pdfs.semanticscholar.org/e7c5/6ebfb76bce8a36d5683c60e2a38dc3147499.pdf>
- [4] Morgan, R. K. (2012). Environmental impact assessment: The state of the art. *Impact Assessment and Project Appraisal*, 30(1), 5–14.  
<https://doi.org/10.1080/14615517.2012.661557>
- [5] Martínez, R. (2010). Propuesta metodológica para la evaluación de impacto ambiental en Colombia. Maestría en Medio Ambiente y Desarrollo. Universidad Nacional de Colombia.
- [6] Nita, A., Fineran, S., & Rozyłowicz, L. (2022). Researchers' perspective on the main strengths and weaknesses of Environmental Impact Assessment (EIA) procedures, *Environmental Impact Assessment Review*, 92, 106690.  
<https://doi.org/10.1016/j.eiar.2021.106690>.
- [7] Otterpohl, R., Grottker, M., & Lange, J. (1997). Sustainable water and waste management in urban areas. *Water Sci Technol*, 35(9), 121-133.  
[https://doi.org/10.1016/S0273-1223\(97\)00190-X](https://doi.org/10.1016/S0273-1223(97)00190-X)
- [8] Lal, R. (2000). Soil management in the developing countries. *Soil Science*, 165(1), 57-72.
- [9] Shakantu, W., Tookey, J. E., & Bowen, P. A. (2003). The hidden cost of transportation of construction materials: An overview. *Journal of Engineering, Design, and Technology*, 1(1), 103-118. <https://doi.org/10.1108/eb060892>
- [10] Shehadeh, A., Alshboul, O., Tatari, O., Alzubaidi, M. A., & Salama, A. H. E. (2022). Selection of heavy machinery for earthwork activities: A multi-objective optimization approach using a genetic algorithm, *Alexandria Engineering Journal*, 61(10), 7555-7569,  
<https://doi.org/10.1016/j.aej.2022.01.010>.
- [11] Zhang, X., Wu, L., Zhang, R., Deng, S., Zhang, Y., Wu, J., Li, Y., Lin, L., Wang, Y., & Wang, L. (2013, February). Evaluating the relationships among economic growth, energy consumption, air emissions, and air environmental protection investment in China. *Renewable and Sustainable Energy Reviews*, 18, 259-270. <https://doi.org/10.1016/j.rser.2012.10.029>

- [12] Wang, C., Shao, N., Xu, J., Zhang, Z., & Cai, Z. (2020). Pollution emission characteristics, distribution of heavy metals, and particle morphologies in a hazardous waste incinerator processing phenolic waste. *Journal of Hazardous Materials*, 388, 121751. <https://doi.org/10.1016/j.jhazmat.2019.121751>
- [13] Tétrault, J. (2016). Agent of deterioration: Pollutants. Canada.ca. <https://www.canada.ca/en/conservation-institute/services/agents-deterioration/pollutants.html>
- [14] Zaman, K., Abdullah, I., & Ali, M. (2016). Decomposing the linkages between energy consumption, air pollution, climate change, and natural resource depletion in Pakistan. <https://doi.org/10.1002/ep.12519>
- [15] Goebel, K., Camargo-Borges, C., & Eelderink, M. (2019). Exploring participatory action research as a driver for sustainable tourism. *International Journal of Tourism Research*. <https://doi.org/10.1002/jtr.2346>
- [16] Fischer, T. B. (2010). *The theory and practice of strategic environmental assessment: Towards a more systematic approach*. Routledge.
- [17] Li, X., Zhu, Y., & Zhang, Z. (2010). An LCA-based environmental impact assessment model for construction processes. *Building and Environment*, 45(3), 766–775. <https://doi.org/10.1016/j.buildenv.2009.08.010>
- [18] Zolfagharian, S., Nourbakhsh, M., Irizarry, J., Ressang, A., & Gheisari, M. (2012). Environmental impacts assessment on construction sites. *Construction Research Congress 2012*, 1750–1759. <https://doi.org/10.1061/9780784412329.176>
- [19] Mannan, M., & Al-Ghamdi, S.G. (2022). Water consumption and environmental impact of multifamily residential buildings: A life cycle assessment study. *Buildings* 2022, 12(1). <https://doi.org/10.3390/buildings12010048>
- [20] Kazaz, B., Schussler, J. C., Dickey, L. C., & Perez, M. A. (2022). Soil loss risk analysis for construction activities. *Transportation Research Record*, 2676(6), 503-513. <https://doi.org/10.1177/03611981221075027>
- [21] Kucher, A., Anisimova, O., & Heldak, M. (2019). Efficiency of land reclamation projects: New approach to assessment for sustainable soil management. *Journal of Environmental Management & Tourism*, X (7(39)), 1568-1582.
- [22] Broujeni, B.R., Omrani, G.A., Naghavi, R., Azadi, F. (2016, December). Construction and Demolition Waste Management (Tehran Case Study). *Journal of Solid Waste Technology & Management*, 6(6): 1249-1252. <https://doi.org/10.48084/etasr.812>
- [23] Sahuí Maldonado, J. A. (2014). El consumo responsable de los recursos naturales como punto de partida para un desarrollo sustentable: Una aproximación crítica. *Hitos de Ciencias Económico Administrativas*, 18(51), 63-72. <https://doi.org/10.19136/hitos.a0n51.314>
- [24] Martínez, J., Mallo, M., Lucas, R., Alvarez, J., & Salvarrey, A. (2005). *Guía para la gestión integral de residuos peligrosos: Fundamentos*.



- [25] Acevedo Agudelo, H., Vásquez Hernández, A., & Ramírez Cardona, D. A. (2012, mayo). Sostenibilidad: Actualidad y necesidad en el sector de la construcción en Colombia. *Gestión y Ambiente*, 15(1), 105-117.
- [26] Lavy, V., Rachkovski, G., & Yoresh, O. (2023). Air pollution exposure increases the likelihood of workplace accidents in construction sites. *Journal of Construction Safety* (in press).  
[https://blogs.lse.ac.uk/businessreview/2023/09/06/air-pollution-increases-the-likelihood-of-accidents-in-construction-sites/?utm\\_source=chatgpt.com](https://blogs.lse.ac.uk/businessreview/2023/09/06/air-pollution-increases-the-likelihood-of-accidents-in-construction-sites/?utm_source=chatgpt.com)
- [27] Wieser, A. A., Scherz, M., Passer, A., & Kreiner, H. (2021). Challenges of a Healthy Built Environment: Air Pollution in Construction Industry. *Sustainability*, 13(18), 10469.  
[https://www.mdpi.com/2071-1050/13/18/10469?utm\\_source=chatgpt.com](https://www.mdpi.com/2071-1050/13/18/10469?utm_source=chatgpt.com)
- [28] Scanlon, B. R., Faunt, C.C., Longuevergne, L., Reedy, R.C., Alley, W.M., McGuire, V.L., & McMahon, P.B. (2012, May). Groundwater depletion and sustainability of irrigation in the US High Plains and Central Valley. *Proceedings of the National Academy of Sciences of the United States of America*, 109(24), 9320–9325.  
[https://pmc.ncbi.nlm.nih.gov/articles/PMC3386121/?utm\\_source=chatgpt.com](https://pmc.ncbi.nlm.nih.gov/articles/PMC3386121/?utm_source=chatgpt.com)
- [29] Alao, J. O., Bello, A., Lawal, H. A., Abdullahi, D. (2024). Assessment of groundwater challenges in arid and semi-arid regions. *Water Sustainability*, 2, 100049.  
[https://www.sciencedirect.com/science/article/pii/S2211714824000360?utm\\_source=chatgpt.com](https://www.sciencedirect.com/science/article/pii/S2211714824000360?utm_source=chatgpt.com)
- [30] Behzad, H. M., Jiang, Y., Arif, M., Wu, C., He, Q., Zhao, H., & Lv, T. (2022). Tunneling-induced groundwater depletion limits long-term ecosystem survival. *Science of the Total Environment*, 811, 152375.  
[https://www.sciencedirect.com/science/article/abs/pii/S0048969721074532?utm\\_source=chatgpt.com](https://www.sciencedirect.com/science/article/abs/pii/S0048969721074532?utm_source=chatgpt.com)
- [31] Preene, M., & Brassington, R.(2003). Potential groundwater impacts from civil engineering works. *Water and Environmental Management Journal*, 17(1), 59–64.
- [32] Kineber, A. F., & Hamed, M. M. (2022). Exploring the sustainable delivery of building projects in developing countries: A PLS-SEM Approach. *Sustainability*, 14(22), 15460.  
<https://doi.org/10.3390/su142215460>
- [33] INEGI (2022). DENUE Establishments Directory.  
<https://en.www.inegi.org.mx/app/mapa/denue/>
- [34] Kemmis, S., McTaggart, R., & Nixon, R. (2014). *The Action Research Planner: Doing Critical Participatory Action Research*. Springer.  
<http://dx.doi.org/10.1007/978-981-4560-67-2>

- [35] Hair, J. F. Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.
- [36] Loh, X., Voon-Hsien, L., Wei-Han, T., Tan, G. W., Hew, J., & Ooi, K. (2022). Towards a cashless society: The imminent role of wearable technology. *Journal of Computer Information Systems*, 62(1), 39-49. <https://doi.org/10.1080/08874417.2019.1688733>
- [37] Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50. <https://doi.org/10.1177/002224378101800104>
- [38] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- [39] Ringle, C. M., Wende, S., & Becker, J. M. S. (2022). *Smart PLS GmbH*. Germany.
- [40] Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Routledge. <https://doi.org/10.4324/9780203771587>
- [41] Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013, March). Partial least squares structural equation modeling: Rigorous Applications, Better Results and Higher Acceptance. *Long Range Planning*, 46, (1-2), 1-12. <https://ssrn.com/abstract=2233795>
- [42] Henseler, J., & Fassott, G. (2010). Testing moderating effects in PLS path models: An illustration of available procedures. In Esposito V. E. Vinzi, W. W. Chin, J. Henseler, & H. Wang. (Eds.) *Handbook of Partial Least Squares*. Springer Handbooks of Computational Statistics (pp. 713-735). [https://doi.org/10.1007/978-3-540-32827-8\\_31](https://doi.org/10.1007/978-3-540-32827-8_31)
- [43] Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business review*, 31(1), 2-24. <https://doi.org/10.1108/EBR-11-2018-0203>
- [44] Falk, R.F., & Miller, N.B. (1992). *A primer for soft modelling*. The University of Akron Press.
- [45] Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares. *European Journal of Marketing*, 53(4), 566-584. <https://doi.org/10.1108/EJM-10-2018-0665>
- [46] RunZe, L., Benitez, J., Zhang, L., Shao, Z., & JiaNing, M. (2024). Exploring the influence of gamification-enabled customer experience on continuance intention towards digital platforms for e-government: An empirical investigation. *Information & Management*, 61(5), 103986. <https://doi.org/10.1016/j.im.2024.103986>.

- [47] Maldonado, G., Juárez, R., & Molina, V. (2024). Las prácticas Lean son la solución para mejorar el rendimiento empresarial en la industria manufacturera de México? *Multidisciplinary Business Review* 17(1), 33-48, <https://doi.org/10.35692/07183992.17.1.4>
- [48] Molina-Morejón, V. M., Maldonado-Guzmán, G., & Fernández-Contreras, L. (2024). The mediation of drivers and practices to overcome barriers to the circular economy. *Scientia Et PRAXIS*, 4(08), 28–63. <https://doi.org/10.55965/setp.4.08.a2>
- [49] Knights, P., Admiraal, J.F., Wossink, A., & Banerjee, P. (2013, July). Economic environmental valuation: An análisis of limitations and alternatives. BIOMOT Project, FP 7 nr, 282625 <http://dx.doi.org/10.13140/2.1.4780.7524>
- [50] Sandford, O. R. R. (1971, August.). The Chilean armed forces: The role of the military in the popular unity government. <https://www.researchgate.net/profile/Oscar-Robinson-Rojas-Sandford/publication/266316986>
- [51] Sentís, I. P. (2011). Evaluación y modelización hidrológica para el diagnóstico de “desastres naturales”. *Gestión y Ambiente*, 14(3), 7-22.
- [52] Goodrum, P.M., Yinggang, W., Fenouil, P. C. (2009, February). A decision-making system for accelerating roadway construction. *Engineering, Construction, and Architectural Management*, 16(2), 116–135. <https://doi.org/10.1108/09699980910938000>
- [53] Yetemen, O., Istanbuluoglu, E., & Vivoni, E. R. (2010). The implications of geology, soils, and vegetation on landscape morphology: Inferences from semi-arid basins with complex vegetation patterns in Central New Mexico, USA. *Geomorphology*, 116(3-4), 246-263. <https://doi.org/10.1016/j.geomorph.2009.11.026>