

DEVELOPING A DATA-DRIVEN FAILURE DECISION-MAKING FRAMEWORK FOR SUSTAINABLE URBAN WATER MANAGEMENT PROJECTS

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Article History:

▪ received 20 April 2024
 ▪ accepted 13 May 2025

Abstract. Several degradation factors significantly impact the durability of water pipes in urban areas. However, limited research has comprehensively prioritized these factors to support data-driven maintenance and renewal decisions. Addressing this gap, this study identifies and ranks the failure factors affecting water pipeline infrastructure. A survey of 125 Egyptian water industry experts was conducted, and the collected data were analyzed using partial least squares-structural equation modeling as the decision-making framework. By incorporating insights from previous research and expert opinions, the research developed a robust failure decision-making model that provided significant insights into the primary factors contributing to water pipeline failures. Model analysis revealed that the "operational factor", with an impact value of 0.543, was the most critical group of factors affecting pipeline failure. Following closely with an impact value of 0.480, was the "static factor". Natural disasters (0.373), climate and weather conditions (0.325), and soil conditions (0.300) also contributed considerably. Following closely were "dynamic loads" (0.276), "aging and environmental factors" (0.250), and "third-party factors" (0.200), which had the least impact on the failure of the pipeline. This study has developed a novel failure decision-making model by synthesizing insights from previous studies, expert opinions, and empirical data on water pipeline failure.

Keywords: sustainable management, decision-making, water pipelines.

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1. Introduction

Water distribution systems (WDSs) are common features of urban and developed societies. These systems influence ecosystems, societies, and their economies. Nonetheless, the dependability and capacity of WDS are premised on the hydraulic conditions within the pipe networks (Hamed et al., 2022; Khadr et al., 2022). For context, the cumulative costs arising from water pipe failures in North America were estimated to be over CAD 6 billion in the past decade, according to Fares and Zayed (2010). WDSs are complex and failures may occur from known and unknown causes (Wolfe, 1946). To mitigate the challenges of replacing and maintaining water pipelines, it is essential to have

access to comprehensive and standardized data from water utilities, which in most cases, are unavailable (Kleiner & Rajani, 1999).

Among the several factors responsible for water pipeline failures, pipe materials play a significant role. Kleiner and Rajani (2001) identified split bells and circumferential failures as critical flaws associated with pipes made from grey cast iron (GCI). Additionally, corrosion is another type of degradation in water pipes (Wilson et al., 2015; Shi, 2018; Jun et al., 2020). Hu and Hubble (2007) and Rajeev et al. (2014) categorized failure factors into external (e.g., frost and traffic-induced loads) and internal factors (e.g., internal

pressures and chemical corrosion), which can lead to longitudinal failures and pinhole and blowout leaks, respectively.

Safe drinking water, which is essential for ensuring public health and safety, is contingent on the integrity of water pipelines. Therefore, a cost-effective method to guarantee public health and safety is to anticipate failures by estimating structural deterioration (Almheiri et al., 2020) and thus minimize damage to ancillary facilities like roads and ground stability (Qi et al., 2018; Abdel-Mottaleb et al., 2019). Recent studies by Elshaboury and Marzouk (2020, 2022), Kerwin et al. (2023), Lu et al. (2023), Shaban et al. (2023), Taiwo et al. (2023), Latifi et al. (2024), and Mohammed Abdelkader et al. (2025) highlighted the role of advanced modeling techniques, including machine learning and hybrid models, in improving the accuracy of pipe failure predictions and risk assessments. These studies offer valuable insights into how new methodologies can enhance the predictive capabilities of deterioration models, thereby contributing to more sustainable infrastructure management practices.

Sustainability, comprising environmental, social, and good governance, is recognized as a crucial driver for economic prosperity (Lichtenthaler, 2023). Many countries struggle to achieve sustainable economic development, as highlighted by Chen et al. (2025). However, developing countries pose unique challenges to the sustainability of water projects. These countries' rapid economic development has increased the water industry's importance in providing necessities, especially in urban areas (Kineber et al., 2022a). The success of the field indicators is rated by cost, quality, and construction project time (Yaseen et al., 2020). Meanwhile, enhancing resource efficiency is a key aspect of environmental innovation, contributing to sustainable project success (UI-Durar et al., 2023).

Several emerging countries have reshaped their water industries to advance their economies. The literature suggests developing nations are upgrading their financial infrastructure (Fang et al., 2020). Many developing nations face enormous challenges with their water sector, which may include failure to achieve water distribution targets, inadequate planning with its attendant cost overruns, and poor sustainability policies. Therefore, the construction sector in most developing countries significantly lags its more developed counterpart in terms of meeting the needs of clients, governments, and sustainability (Jekale, 2004).

In the Middle East, despite the tremendous human resources available in Egypt, its market is characterized as high-risk due to several challenges not limited to poor wages, high unemployment, insecurity, and infrastructural deficit (Barakat et al., 2016). Despite efforts to modernize its water infrastructure, WDSs are constantly under immense pressure due to aging pipelines, poor maintenance strategies, lack of robust predictive models for failure assessment and a rapidly growing urbanization drive to cater for its exploding population. This has led to fre-

quent pipe failures and high maintenance costs (Elshaboury et al., 2020).

To develop efficient and sustainable WDSs to meet the needs of a developing nation like Egypt, it is essential to investigate the crucial factors responsible for the deterioration and failure of water pipelines. Available literature data suggests that most of the research was devoted to exploring and analyzing pipeline conditions in developed nations. Limited studies have explored the needs peculiar to developing nations, such as Egypt. Accordingly, the present study will address this gap by developing a novel failure decision-making model based on the partial least squares-structural equation modeling (PLS-SEM) technique to identify and categorize the critical factors responsible for water pipeline failure in Egypt. The study leveraged the insights from 125 water professionals and incorporated recent advancements in predictive modeling. The outcomes of this research offer valuable insights into asset management strategies in other developing regions facing similar challenges. Ultimately, by identifying critical factors and leveraging data-driven methodologies, this study has contributed to enhancing the sustainability and resilience of urban water distribution systems.

The remaining sections of this paper are structured thus: a concise literature review summary is presented in Section 2, which highlights some previous studies on related topics. The research methodology is addressed in Section 3, while study findings are aggregated in Section 4. A comprehensive analysis and discussion of the research findings are provided in Sections 5, 6 and 7. The final section (Section 8) summarizes the key findings, provides a critical evaluation of the study's limitations, and proposes suggestions for future research directions.

2. Pipe failure: assessment of critical factors

Cast iron (CI) was widely applied in WDSs prior to the development of ductile iron (DI) materials (Mora-Rodríguez et al., 2014). A study in Kelowna City, British Columbia, Canada, revealed that during both winter and summer; approximately 9% of metallic water mains in the WDSs were at high risk (Kabir et al., 2015a). The choice of material significantly impacts failure rates (Kutyłowska & Hotłoś, 2014). Additional research into how the materials used in water distribution pipelines affect their failure rate is provided by Pietrucha-Urbanik (2015). The results of this investigation showed that iron and polyvinyl chloride (PVC) pipes were equally prone to failure, each contributing to 33% of total pipeline failures. In contrast, CI pipes accounted for 60% of failures in primary water pipes attributed to corrosion. On the other hand, the most prominent failure type associated with polyethylene (PE) and reinforced concrete pipes were joint failures, as reported by Pratt et al. (2011). Further analysis revealed that pipe materials influenced failure rates. Hence, CI had the highest failure rate, while asbestos cement (AC), galvanized steel, and polymeric pipes (PVC and PE) recorded lower failure rate.

In addition to pipe materials, pipe diameter affects water mains failure (Zamenian et al., 2017). Smaller diameter pipes were found to exhibit higher failure rates (Shirzad et al., 2014; Jun et al., 2020; Robles-Velasco et al., 2020). Other studies concluded that a 10% reduction in pipe thickness resulted in a 50% reduction in the pipe's useful life (Tavakoli et al., 2020). Thus, the relationship between wall thickness, diameter, and material integrity is critical in understanding the overall failure rate of pipelines. Water distribution pipeline failure is also linked to traffic loads and the pressure of the surrounding soil (Moerman et al., 2016; Aşçilean et al., 2018; Garmabaki et al., 2019). Heavy vehicle traffic can have a negative effect on water pipelines less than 300 mm in diameter, as observed by Aşçilean et al. (2018).

Some studies correlated water pipe lengths with their failure rates (Kleiner et al., 2007; Zangenehmadar & Moselhi, 2016a; Almheiri et al., 2020). Longer pipes were reportedly prone to failure than shorter ones (Yamijala et al., 2009). Furthermore, soil pressure on buried pipes and depth of burials played significant roles in pipeline failure, as highlighted by Jun et al. (2020). However, Wilson et al. (2015) asserted that the type of pipe material appeared to influence this behavior as CI pipes were prone to failure at a shallower depth. In addition, pipe age played a significant role in the failure of pipelines (Kleiner & Rajani, 2001; Almheiri et al., 2020). On this, corrosion was the primary cause of age-related pipe failure in metallic pipes (Boxall et al., 2007). These findings emphasize the need for a multi-dimensional risk assessment approach, where factors like material, length, age, and depth interact to influence failure rates.

Natural events, such as floods, earthquakes, and heavy rainfall may contribute to accelerating the deterioration of pipelines in WDSs (Gassman et al., 2017). Environmental disasters, therefore, play a significant role in accelerating pipe failure, emphasizing the need for resilience planning in water distribution infrastructure. Similarly, climate conditions, such as minimal antecedent precipitation index and net evaporation (Gould et al., 2011), affect water pipeline failure. Other studies have identified CI corrosion, precipitation shortfall, wind speed, and frost depth as factors responsible for pipeline failure in WDSs (Pratt et al., 2011; Claudio et al., 2014).

Fluctuation in air temperature accelerated the failure of asbestos cement water pipes submerged in clayey soil (Chaudry, 2009). The influence of soil type on water pipe failure has also been investigated. Higher failure rates were recorded in acidic and peaty soils compared with other soil types, according to Farewell et al. (2018). Dry soil conditions and soil movement in summer increase water pipe failure rates (Arsénio et al., 2015; Qu et al., 2019; Barton et al., 2020). Wols et al. (2014) indicated that severe droughts and high temperatures could accelerate the degradation of water pipes. A corroborating study found that carbon steel, DI, and PE pipes experienced higher failure rates in summer than in cooler months (Chowdhury

& Rajput, 2016). However, DI, PVC, and GCI pipes were more likely to fail at lower temperatures while the failure of PE water pipes showed no correlation with temperature (Wols et al., 2019). Relating to corrosion, soil resistivity played a crucial role in CI pipe failure according to Kabir et al. (2015b). Therefore, soil conditions and weather conditions are factors that greatly impact the failure of pipelines in WDS.

Water quality, construction methodologies, and maintenance schedules played critical roles in the failure of water mains (Hu & Hubble, 2007). Other crucial failure factors in the literature included groundwater, water quality, oxygen concentration, pipe placement and materials, and stray electrical currents, as reported by Zangenehmadar and Moselhi (2016b). According to Robles-Velasco et al. (2020), the primary factors influencing pipeline failures, in order of significance, are pipe material, length, age, and past breaks. On the other hand, Almheiri et al. (2020) identified the critical factors affecting pipeline failures as electrical resistivity, installation depth, pipe length, landslides, improper operations, earthquakes, and flow velocity. Jun et al. (2020) emphasized that water alkalinity, pipe age, residual chlorine, pipe thickness, water pH, pipe depth, pipe diameter, and water temperature significantly impacted the structural stability of steel pipes. These diverse contributing factors highlighted the multifaceted nature of water pipe failures and underscored the need for comprehensive, multi-variable approaches in failure prediction models.

3. Originality of the study

This study enhances infrastructure management by identifying key factors contributing to pipeline failures, helping stakeholders reduce costs, improve quality, and enhance sustainability. After reviewing the existing literature several critical research gaps emerge, highlighting the need for a more targeted investigation into water pipeline failures. While prior research has examined pipeline failures in developed nations, a critical gap remains in Egypt's construction sector, where projects often face budget overruns, delays, and sustainability challenges (Kineber et al., 2022a). As a result, a significant knowledge gap exists in identifying the factors contributing to water pipeline infrastructure failures, particularly in the context of Egypt's construction sector. The significance of this study is underscored by the fact that existing models may not apply to the Egyptian context since they were premised on the data derived from a different environmental perspective, material, and operational conditions. As such, applying such models may lead to inaccurate assessments and inadequate maintenance strategies. Furthermore, the significance of these related factors within their respective clusters has not been thoroughly investigated. A more detailed examination of how these failure causes interact would allow for a deeper understanding of their combined effects and help prioritize mitigation strategies. To bridge these

knowledge gaps, this research seeks to develop a data-driven decision-making model that systematically identifies and quantifies the primary factors contributing to water pipeline failures in the Egyptian context. The primary objectives of this research are to:

1. Identify and classify the critical factors contributing to water pipeline failures within the Egyptian construction sector.
2. Analyze the interrelationships among these factors and determine their relative significance within their respective clusters.
3. Develop a predictive model using PLS-SEM to evaluate the impact of these factors on pipeline deterioration.
4. Provide actionable insights for infrastructure managers, policymakers, and industry stakeholders to optimize asset management and maintenance strategies.

This study employs a rigorous mathematical methodological approach, specifically utilizing PLS-SEM. Unlike traditional statistical techniques, which may struggle to capture the complex interdependencies between multiple variables, PLS-SEM enables the modeling of the relationship between the primary factors contributing to water pipeline failures. By offering a region-specific, data-driven approach, this research contributes to bridging the gap between global deterioration models and localized infrastructure challenges. Consequently, the study introduces a cost-efficient, environmentally sustainable approach to pipeline failure assessment, applying PLS-SEM for the first time to evaluate failure factors in water distribution systems. This data-driven methodology optimizes maintenance strategies and infrastructure investments.

Though conducted in Egypt, the findings apply to other developing nations with similar challenges, offering a scalable framework for improving pipeline sustainability. By integrating predictive modeling with failure risk assessment, this research demonstrates how advanced techniques can drive sustainable infrastructure development in resource-constrained environments. With the availability of data, mathematical modeling can be used to support global sustainability initiatives to mitigate the risk associated with water pipeline failure (Farrokhirad & Gheitarani, 2024). PLS-SEM is an important tool that can explain the complex relationship between the various factors responsible for pipeline failure. Furthermore, populating PLS-SEM with data on pipe degradation, environmental constraints, operational controls, and maintenance schedules could result in models for facilitating resource optimization and scheduling proactive maintenance practices. Overall, such models could effectively ensure the longevity of pipelines in WDSs.

Additionally, the current study identifies some of the challenges unique to pipeline failure in developing countries like Egypt, where rapid urbanization, aging infrastructure, and economic constraints exert considerable pressure on existing WDS networks. Existing literature on water pipeline failures is biased towards developed nations

(Kineber et al., 2022a; Mohandes et al., 2022), highlighting the need for studies that address the distinct needs and circumstances of developing countries. Therefore, this study fills such a gap by leveraging PLS-SEM to offer practical recommendations for improving pipeline infrastructure and resilience. Ultimately, this study contributes to informed policymaking and infrastructure planning by assessing the economic, environmental, and operational implications of pipeline failures. Its findings are expected to guide engineers and policymakers in formulating and implementing evidence-based solutions for sustaining WDS in developing nations.

4. Research design and methodology

This study aims to investigate and determine the most critical factors responsible for water pipeline failures in a developing nation with an emphasis on Egypt. To achieve this aim, the research deployed a three-pronged quantitative approach: (1) reviewing the existing literature to summarize and determine the key factors influencing pipeline failure (Inputs), (2) designing and administering a questionnaire to gather empirical data, and (3) applying SEM to explore the relationships between the identified factors (Outputs). An overview of the methodology is presented in Figure 1. PLS-SEM was chosen primarily due to its robustness in handling complex relationships between multiple variables in infrastructure-related studies and its ability to handle small to medium-sized (Hair et al., 2011). This method is well-suited for exploring causal relationships and assessing the relative influence of various factors affecting pipeline failure. Compared to conventional regression analysis, PLS-SEM offers a distinct advantage suitable for an adaptable and precise modeling framework. The methodology design is appropriate and justified, given the study's focus on assessing the current state of water pipeline deterioration and providing insights for immediate action. Adapting the research of Almheiri et al.

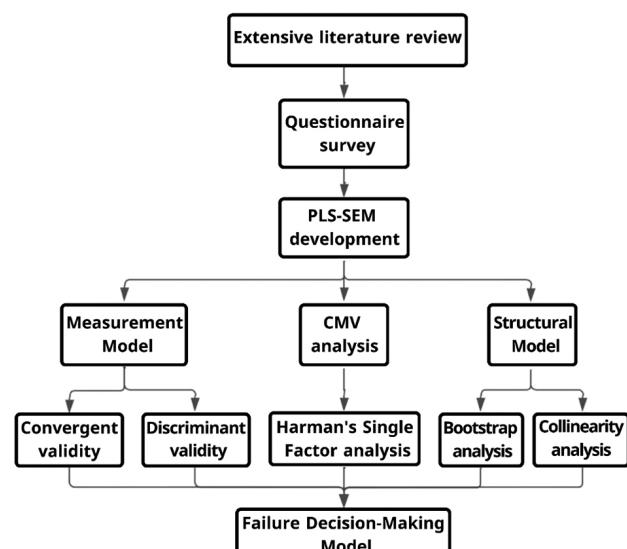


Figure 1. Structure of the methodology

(2023), a comprehensive summary of the causes of water pipeline failure is presented in Table 1. A questionnaire was administered to 125 water pipeline stakeholders, including experts and professionals involved in the planning, designing, and management of water pipeline infrastructure. Each respondent rated the severity of pipeline deterioration factors using a Likert scale. To gather informed perspectives, this study employed stratified sampling across Egypt's water pipe sectors, targeting professionals with decision-making roles in water projects. Using the primary informant method, participants were selected based on: (1) their expertise in water piping projects, (2) current hands-on experience, and (3) significant project involvement. These criteria followed established guidelines

in construction research (Ranesh, 2014; Kim et al., 2016; Hu et al., 2016). Results of the systematic review were utilized to construct research hypotheses that were validated using PLS-SEM as a confirmatory analysis tool (Shields & Tajalli, 2006).

4.1. Structural equation modeling (SEM)

SEM was selected as the modeling technique in this research based on its successful deployment in many building-based research studies (Durdyev et al., 2018; Yin et al., 2022). The interrelationships between the different failure factors were analyzed using the PLS model, which included both reflective and formative factors. PLS-SEM has proven effective in establishing relationships between factors that

Table 1. Key factors contributing to water pipeline failure

Main Factor	Code	Sub-Factor	Main Factor	Code	Sub-Factor
Static	S1	Pipe material	Natural disasters	ND1	Seismic activity
	S2	Pipe lining/coating		ND2	Extreme rainfall events
	S3	Pipe installation		ND3	Floods
	S4	Dissimilar metals		ND4	Landslides
	S5	Type of joint		ND5	Earthquakes
	S6	Pipe diameter		ND6	Environmental disturbance
	S7	Pipe length	Aging and environmental	O1	Pipe age
	S8	Depth of installation		O2	Wall thickness
	S9	Pipe location		O3	Groundwater
	S10	Pipe manufacture		O4	Stray electrical currents
Dynamic loads	D1	Internal and external corrosion	Operational	O5	Time
	D2	Prior pipe breaks		O6	Ferrous corrosivity scale
	D3	Frost loading		OP1	Water pressure
	D4	Traffic loads		OP2	Operation and maintenance practices
Soil conditions	SC1	Soil type		OP3	Leakage
	SC2	Backfill material		OP4	Water pH
	SC3	Soil pH		OP5	Inadequate design
	SC4	Soil movement		OP6	Improper installation
	SC5	Soil corrosivity		OP7	Water hammer
	SC6	Soil moisture		OP8	Manufacturing defects
	SC7	Soil weights		OP9	Operating pressure
	SC8	Soil moisture deficit		OP10	Replacement rate
	SC9	Electrical resistivity		OP11	Cathodic protection
	SC10	Soluble salts (NaCl)		OP12	Water flow velocity
Climate and weather conditions	CW1	Temperature/season variations	Third-party	OP13	Water quality
	CW2	Days air frost		OP14	Oxygen content
	CW3	Soil moisture deficit		OP15	Water alkalinity and conductivity
	CW4	Mean daily temperature		OP16	Residual chlorine
	CW5	Frost heave		T1	Regulations and policies
	CW6	water temperature		T2	Urbanization
	CW7	Rainfall		T3	Restrictions
	CW8	Ground temperature		T4	Social needs
	CW9	Net evaporation		T5	Cost
	CW10	Minimum antecedent precipitation index			
	CW11	Wind gust			
	CW12	Rain deficit			
	CW13	Frost depth			

were previously considered independent or unconnected (Sarhadi & Rad, 2020). In the PLS-SEM analysis, the following critical evaluations were performed: assessment of common method variance, validation of the measurement model, and evaluation of the structural model, based on the recommendations by Kineber et al. (2023).

4.2. Common method bias (CMB)

To identify potential errors and biases in the data-gathering process, a common method bias (CMB) assessment was performed. This is crucial for identifying common method variance (CMV)-related problems and interpreting error investigation results accurately (Kineber et al., 2022b). Consistent with Harman's approach (Oke et al., 2022), a systematic and in-depth analysis of a single factor was performed. CMB was mitigated through the inclusion of multiple data sources and ensuring anonymity in survey responses, thus enhancing data quality and reducing the risk of biased reporting.

4.3. Measurement model

As noted by Al-Ashmori et al. (2020), the measurement model specifies the explicit relationships between observable variables (factors) and their corresponding latent constructs. Validation could be defined as reviewing and assessing the measurement model (Zaid Alkilani, 2018). The PLS method was used to assess the reliability and validity of the measurement (factor) sets. To examine the reflective first-order model, estimates of indicator reliability, composite reliability (CR), average variance extracted (AVE), and discriminant validity were obtained (Leguina, 2015). A robust assessment of construct reliability was achieved through the use of Cronbach's alpha, composite reliability, and AVE. Cronbach's alpha (α) was used to evaluate the consistency of a construct (Aibinu & Al-Lawati, 2010). Al-Otaibi and Kineber (2023) defined Cronbach's alpha (α) thus:

$$\alpha = \frac{N - \bar{c}}{1 + (N - 1) - \bar{c}} \quad (1)$$

with N being the total count of factors and \bar{c} representing the mean correlation between the factors.

To ensure greater reliability and validity in the context of our study, composite reliability was equally performed in addition to Cronbach's alpha, as it accounted for factor loadings. The following expression describes the composite reliability (ρ_c) (Wong, 2013):

$$\rho_c = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum \text{var}(\epsilon_i)}, \quad (2)$$

where ρ_c represents the composite reliability score, λ_i denotes the loading of each item on the latent construct, and $\text{var}(\epsilon_i) = 1 - \lambda_i^2$ describes the variance in the loadings. To ensure reliability, $\rho_c \geq 0.7$ is required for any research, although a slightly lower threshold of 0.6 is acceptable for exploratory studies.

Additionally, the AVE was used to test the latent variables' convergent validity (Henseler et al., 2016). As described in Eqn (3), the AVE is a popular metric for proving that parts of a model converge.

$$\text{AVE} = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum \text{var}(\epsilon_i)}, \quad (3)$$

where λ_i represents its component loading on a latent construct and $\text{var}(\epsilon_i) = 1 - \lambda_i^2$. The AVE, calculated through the variance explained by each item, was found to meet the established threshold for convergent validity.

4.4. Structural model

The structural model employed in this study facilitated the simultaneous comparison and assessment of multiple interrelated pipeline failure factors. Furthermore, it was used to build the framework for testing the reliability of water pipelines (Amos et al., 2021). This research employed a structural model that was primarily based on two key approaches:

■ **Collinearity analysis** focuses on the extent to which one or more variables (factors) can explain or predict the effect of another (Hair et al., 2011). To prevent inaccurate results due to collinearity, the variance inflation factor (VIF) was determined. A $\text{VIF} \leq 5$ indicated acceptable model stability (Aibinu & Al-Lawati, 2010).

■ **The bootstrapping analysis** was employed to estimate the variance of data points within sub-samples rather than relying on parametric assumptions. Bootstrapping is a resampling method frequently used in sampling research, whereby a subset of a larger variable dataset is used to determine statistical properties, such as structure or regression coefficients. Therefore, in this study, the bootstrapping technique was applied with 5,000 resamples to ensure the robustness of the estimated coefficients. In this instance, the internal relationship between ξ , μ , and ϵ_1 in the structural model can be expressed as a linear equation (Zaid Alkilani, 2018):

$$\mu = \beta \xi + \epsilon_1, \quad (4)$$

where β is the path coefficient, while ϵ_1 signifies the residual variance. This implies that the magnitude of coefficients obtained from multiple regression analysis is directly comparable to those from standardized regression analysis.

5. Results

5.1. Common method bias

A single-factor analysis was conducted to assess the variability explained by the proposed model, utilizing the standard method outlined by Strandholm et al. (2004) as a basis for comparison. Notably, Oke et al. (2022) found that the typical technique bias did not significantly affect

results when the combined variance of variables was less than 50%. Given that the common method bias was below 50%, the study's conclusions remain unaffected. The results show that the first set of components explains 28.65% of the overall variance (Durdyev et al., 2018).

5.2. Measurement model

5.2.1. Convergent validity

The measurement model assesses the coherence and consistency of multiple factors that collectively capture a single underlying concept. The evaluation of construct validity is conducted concerning the measurement model. The suggested constructs' convergent validity can be assessed in PLS-SEM using the following tests (Aibinu & Al-Lawati,

2010): "composite reliability scores (p_c), Cronbach's alpha (α), and average variance extracted (AVE)". According to Table 2, the composite reliability scores for all factors exceeded the minimum acceptable level of 0.60, confirming their reliability (Amos et al., 2021). The results presented in Table 2 indicate that all factors exhibit adequate reliability, as evidenced by composite reliability scores surpassing the recommended threshold of 0.60. The AVE was also utilized to evaluate the construct variables' convergence validity. If the AVE is greater than 0.5, the measurement variables capture at least 50% of the variance (Amos et al., 2021; Tangi et al., 2021). As can be seen in Table 2, the AVE estimates in this study are more than 50% across the board. The measurement model is proven to have converged and be internally stable by these findings. This also ensures

Table 2. Validity and reliability analyses

Main factor	Factors	Cronbach's alpha	Composite reliability	AVE	Main factor	Factors	Cronbach's alpha	Composite reliability	AVE	
Static	S1	0.7	0.78	0.55	Natural disasters	ND1	0.74	0.84	0.58	
	S2					ND2				
	S3					ND3				
	S4					ND4				
	S5					ND5				
	S6					ND6				
	S7				Aging and environmental	O1	0.86	0.82	0.63	
	S8					O2				
	S9					O3				
	S10					O4				
Dynamic loads	D1	0.75	0.87	0.65		O5				
	D2					O6				
	D3					OP1				
	D4					OP2				
Soil conditions	SC1	0.79	0.76	0.54	Operational	OP3	0.745	0.83	0.64	
	SC2					OP4				
	SC3					OP5				
	SC4					OP6				
	SC5					OP7				
	SC6					OP8				
	SC7					OP9				
	SC8					OP10				
	SC9					OP11				
	SC10					OP12				
Climate and weather conditions	CW1	0.86	0.74	0.57	Third-party	OP13	0.675	0.84	0.67	
	CW2					OP14				
	CW3					OP15				
	CW4					OP16				
	CW5					T1				
	CW6					T2				
	CW7					T3				
	CW8					T4				
	CW9					T5				
	CW10									
	CW11									
	CW12									
	CW13									

that the measurement components used to evaluate each construct measure that construct and not another in the research model. Although Wong (2013) recommends aiming for a score of 0.70 for external load, a value of 0.50 or higher is also acceptable if they are justified by analysis. Table 2 and Figure 2 display the data collected from the first model's external loads.

5.2.2. Discriminant validity

Assessing discriminant validity has become a crucial aspect of SEM research (Shah & Goldstein, 2006). This assessment verifies the empirical uniqueness of the construct under investigation, ensuring it is distinct from other related concepts (Shook et al., 2004). To evaluate discriminant validity, this research employs the following methodologies: Fornell-Larcker criteria, Hetrotrait-Monotrait criterion ratio (HTMT), and cross-loadings. Table 3 presents data that validates the discriminant validity of factor constructions using the Fornell and Larcker method. Specifically, the square root of the AVE exceeds the correlations between the construct and its indicators/variables, as recommended by Durdyev et al. (2018).

The HTMT criterion ratio offers an alternative means of assessing discriminant validity in variance-based SEM. By estimating the correlation between two constructs, assuming measurement accuracy, the HTMT method provides a correlation between constructs. Following the recommendation in the research of Tenenhaus (2008), this study employed HTMT to evaluate discriminant validity. Scores between 0.85 and 0.90 indicate a distinct difference between constructs, whereas values less than 0.85 or greater than 0.90 imply dissimilarity or similarity, respectively. The results, presented in Table 4, confirm that the examined components exhibit sufficient discriminant validity.

5.3. Structural model

The occurrence of unexpected correlations among measurements of formative measurement models is a common phenomenon, while the factors in this study are conceptualized as formative. The results indicate that all VIF values are below the recommended threshold of 3.5. To evaluate the statistical significance of the model's hypotheses, the researchers have utilized the bootstrapping technique (Das et al., 2021; Mohandes et al., 2022). Connection co-

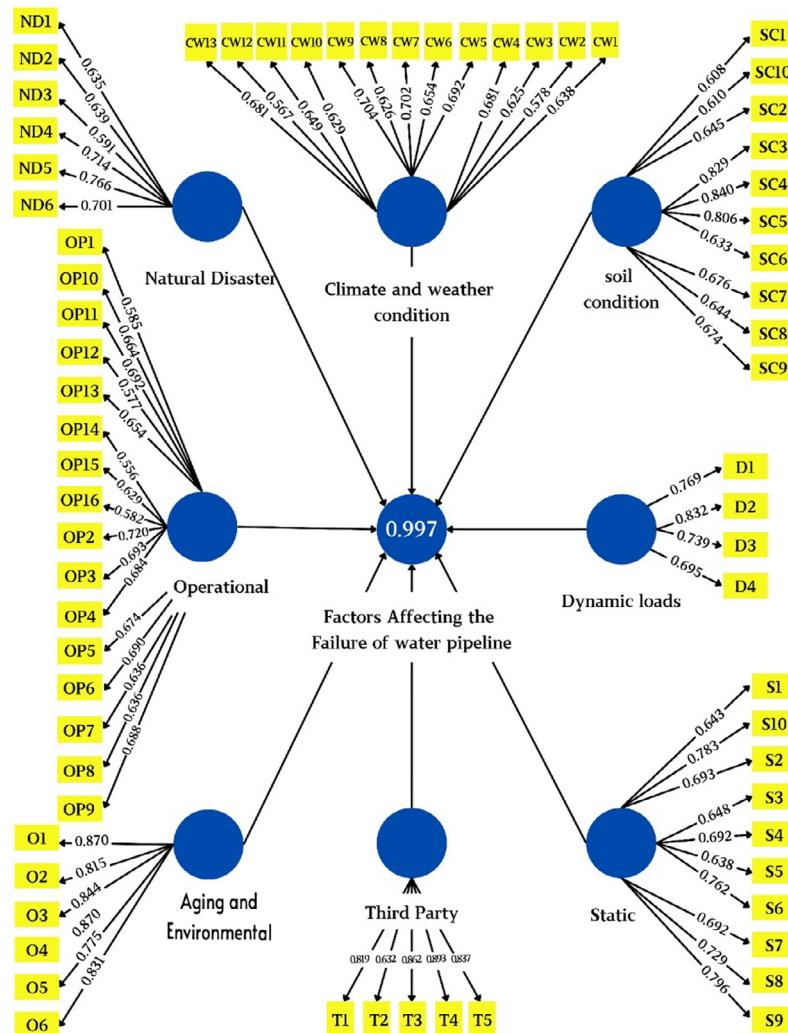


Figure 2. The PLS model

Table 3. Discriminant validity analysis

Construct	Static	Dynamic loads	Soil conditions	Climate and weather conditions	Natural disasters	Aging and environmental	Operational	Third-party
Static	0.665							
Dynamic loads	0.383	0.789						
Soil conditions	0.275	0.254	0.76					
Climate and weather conditions	0.344	0.515	0.226	0.677				
Natural disasters	0.375	0.401	0.169	0.604	0.635			
Aging and environmental	0.339	0.165	0.191	0.202	0.192	0.538		
Operational	0.145	0.262	0.077	0.217	0.337	0.071	0.814	
Third-party	0.292	0.245	0.137	0.292	0.736	0.156	0.371	0.835

Note: for clarity, the bold digits in the text represent the square root of the average values.

Table 4. Discriminant validity (HTMT)

Constructs	Creativity phase	Evaluation phase	Function phase	Natural disasters	Operational	Static	Third-party	Workshop dynamics
Creativity phase								
Evaluation phase	0.339							
Function phase	0.247	0.288						
Natural disasters	0.301	0.84	0.291					
Operational	0.321	0.844	0.203	0.786				
Static	0.617	0.303	0.253	0.3	0.301			
Third-party	0.271	0.301	0.105	0.279	0.383	0.193		
Workshop dynamics	0.23	0.284	0.164	0.337	0.726	0.224	0.421	

efficients represent the magnitude of influence between paths (Adabre et al., 2021). Standard errors of path coefficients were estimated using bootstrapping in SmartPLS 3.2.7 based on the confirmatory factor analysis. Therefore, 5000 subsamples corroborate a proposition by Henseler et al. (2016). The PLS model's single structural equation (Eqn (1)) captures the internal relationships among the constructs. This study investigated the significance of the path coefficients for the endogenous construct, utilizing standardized p-values (Wong et al., 2020). Figure 3 presents these findings, including the results of the bootstrapping analysis. It is speculated that several factors can be attributed to the sum of these thoughts. Figure 3 shows that there are eight first-order subscales for the failure factors, namely static, dynamic loads, natural disasters, climate and weather, soil conditions, aging and environmental, operational, and system integration. These subscales demonstrate a significant path coefficient β for third-party involvement.

6. Discussion

The quality of infrastructure projects, especially water projects, in Egypt has been plagued with issues and paradoxes, as it has been in many other developing countries. This flags the need for principles to identify and explore the failure of water projects. All eight failure factors' com-

ponents significantly impact the implementation of water projects, as shown by the presented model. The next sections show how the suggested model can be used to eliminate each of these variables.

The PLS-SEM analysis indicates that "operational" factors are the most significant contributors (coefficient of 0.543) to the failure of water pipelines. Pipeline failure or deterioration may result when actual demand outstrips planned demand at the various nodes (Bouchart & Goulter, 1991). Other sub-factors related to "operational" factors include poor connection, technical incompetence, and installation of substandard pipes. When these factors are triggered, leaks may occur that can have a direct impact on water loss and water quality (Pietrucha-Urbanik, 2015; Yazdekhasti et al., 2017). Studies have shown that the number of connections in a WDS is inversely proportional to the rate of water loss (Alkasseh et al., 2013).

6.1. Static

The influence of "static" factors is quite significant and is ranked the second most influential group of factors on pipeline failure having an external coefficient of 0.480. Relating to "static factors" are pipe material, joint type, installation depth, and pipe locations, which greatly influence pipeline failure (Pietrucha-Urbanik, 2015). When pipelines in WDS fail, leakages may occur while water quality deteriorates (Pietrucha-Urbanik, 2015; Yazdekhasti et al., 2017).

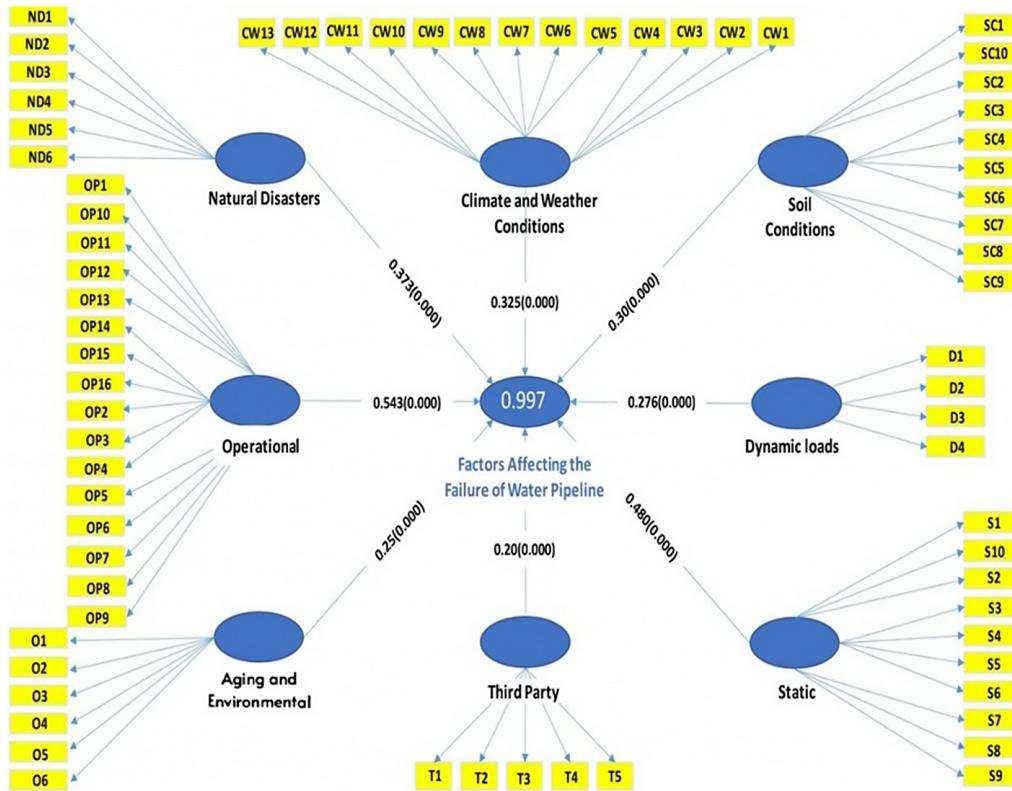


Figure 3. Path analysis

However, studies have shown that the rate of water loss does not directly correlate with the number of connections in a WDS (Alkasseh et al., 2013). Additionally, studies have established variability in the behavior of pipe materials under different atmospheric and geographical conditions. Therefore, it is important to investigate the response of each material type to the diverse conditions (Almheiri et al., 2023). Except for air-conditioning pipes, research indicates that lower average air temperatures are associated with higher failure rates in water pipes (Wilson et al., 2015, 2017).

6.2. Natural disasters

Factors categorized as “third-party” have a significant contribution to the failure of pipeline. With a significant coefficient of 0.373, this group of factors is ranked third on the scale of severity of failure factors. Barton et al. (2020) identify some of the factors contributing to iron pipe failures including air frost duration, pipe diameter, temperature, and soil moisture. Moreover, the failure of water pipes can be influenced by a range of other factors, such as oxygen levels, groundwater, manufacturing processes, water quality, pipe location, and electrical currents (Zangenehmandar & Moselhi, 2016b; El-Abbasy et al., 2019). Research by Almheiri et al. (2023) establishes a strong relationship between corrosion-based water pipe failures and various dynamic factors, such as precipitation levels, and ground temperature. To better understand the dynamics of water pipe degradation, the current study discretizes failure evaluation with each discrete representing one month.

6.3. Climate and weather conditions, soil conditions and others

The fourth, fifth, and sixth causative factors are related to “climate and weather conditions”, “soil condition”, and “aging and environmental” with an external coefficient of 0.325, 0.3, and 0.25, respectively. Rowe (2005) emphasizes the importance of accounting for “climate and weather conditions” when designing, maintaining, and operating pipelines in WDSs. Stress can be induced in pipes due to simultaneous expansion and contraction when temperatures vary widely. Therefore, such stress buildup can eventually lead to pipe cracks or leaks (De Villiers, 2015). Additionally, soils have varied responses to moisture and temperature fluctuations leading to different expansion and contraction rates. These soil movements can exert significant forces on buried pipes, leading to shifts, misalignment, or even damage to the pipes.

6.4. Dynamic loads

The seventh factor is related to “dynamic loads” with an external coefficient of 0.276. Dynamic loads refer to forces and stresses that are not constant but change over time (Harris, 1958). These loads can result from various sources that affect pipelines like water hammer. A water hammer is a sudden increase in pressure within a pipeline caused by an abrupt stop or change in water flow direction. A water hammer can stress pipe walls and joints significantly, potentially leading to leaks or even pipe ruptures (Ghidaoui et al., 2005). To mitigate water hammer, engineers use

various techniques, such as installing surge tanks, pressure relief valves, or water hammer arrestors (Choon et al., 2012). On the other hand, pipelines buried beneath roads or near heavy traffic areas can experience dynamic loads from passing vehicles (Wang et al., 2019). These loads can lead to soil settlement and compaction, affecting the pipeline's integrity.

6.5. Third-party

The least severe impact on pipeline failures is attributed to "third-party" factors, which exhibit an external path coefficient of 0.20. These "third-party" factors include social needs, excavations, urbanization, regulations, cost, and other restrictions, which can affect the integrity of pipelines (Garmabaki et al., 2019). Therefore, pipeline management requires a holistic approach that will factor in the influences of this group of factors. Successful management requires technical expertise in pipeline engineering and effective communication and collaboration with stakeholders, including government agencies, communities, and third-party organizations.

7. Implications

7.1. Managerial implications

The findings of this study have highlighted the importance of categorizing pipeline failure factors to establish a benchmark framework for successfully implementing water projects, especially in developing countries. The existing environmental and sustainable performance framework, established in 2011 post-Arab spring (Aboelmaged, 2018), can be updated with a more modern framework. For Egypt to achieve economic sustainability, water projects must be efficiently implemented (Laukkonen & Tura, 2020). The findings of the current research can be adopted to achieve Egypt's economic development strategy, which prioritizes the establishment of a sustainable, stable, and competitive economy among the world's top 30 (Daoud et al., 2018). Although the methodology utilized in this study focuses on Egypt, it can nevertheless be replicated in other developing nations, particularly those with comparable infrastructure development strategies, to facilitate the implementation of water projects (Aghimien et al., 2018). Developing nations face unique challenges in addressing environmental concerns due to substantial financial burdens (Pham et al., 2020). The model presented here has the potential to support these nations in incorporating sustainability into WDS construction project design to promote environmental responsibility (Zainul-Abidin & Pasqure, 2003; Abidin & Pasqure, 2007). This study makes significant contributions and has far-reaching implications for the construction sector, some of which are discussed below:

- It provides a database of the critical elements and factors contributing to water pipeline infrastructure failure, which can aid owners, consultants, and contractors in evaluating water projects.

- The scientific evidence presented here could serve as a roadmap for Egypt and other developing nations to implement water infrastructure projects.
- Developed countries (Australia, United Kingdom, Hong Kong, and the United States) and other countries (Saudi Arabia, Malaysia, and China) have been the main research focus into various critical factors influencing water pipeline infrastructure failure. As a result, there is a dearth of studies on the implementation of water projects in a developing country and no research exists on the critical factors influencing water pipeline infrastructure failure in the Egyptian infrastructure sector. This study explains why Egyptian water projects can now be linked to the country's infrastructure. The reliability of local water projects can thus be improved, and the knowledge gap can be filled by discussing the use of infrastructure.
- This research provides a useful tool that can aid decision-makers in the objective creation of water projects. This research is the first to propose using PLS-SEM to predict the likelihood of success or failure in the Egyptian water pipeline infrastructure. Therefore, this strategy can potentially revolutionize water projects, especially in underdeveloped nations. Although this study focused on Egypt, the anticipated paradigm shift is expected to have similar implications for other developing nations, presenting comparable challenges and constraints.
- This research provides valuable insights that can contribute to the improvement and expansion of Egypt's water infrastructure. Our research explains why it is important to allocate resources to water projects the right way and cut costs where they are not needed. As a result, the project's cost, timeline, and effectiveness can be centered on thanks to the design and implementation of the planned methods. Improving a project's sustainability greatly benefits society over time.
- A rule of thumb or standard has been established because of this study that can be used to lessen issues arising over a project's implementation. Expenditures, project completion, and hazy requirements were all factors. The findings of this study offer valuable insights for business owners and managers, enabling them to develop a comprehensive understanding of the proposed model and its practical applications. This knowledge can inform strategic decision-making and ultimately enhance the prospects of successful project outcomes.

7.2. Theoretical implications

Recent trends highlight the growing popularity of environmentally friendly business models (Broccardo & Zicari, 2020) though this concept is not completely new (Baldassarre et al., 2020). The model proposed in this study highlights and ranks the severity of the critical factors influ-

encing the failure of water pipeline infrastructure. In the Egyptian context, previous studies have not examined the critical factors influencing water pipeline infrastructure failure. Therefore, the model developed here can be deployed to overcome the present obstacles militating against the effective implementation of water projects in Egypt. To begin with, the critical factors influencing water pipeline infrastructure failure are experimentally identified in this study to aid in implementing water projects in the construction business. Researchers can pivot on this study to learn more about the critical factors influencing water pipeline infrastructure failure in developing countries. The theoretical components of this research provide a foundational mathematical framework for understanding the critical factors influencing water pipeline infrastructure failure, with significant implications for Egypt and other developing nations. Using a novel PLS-SEM methodology, this research identifies and ranks eight key factors influencing water pipeline infrastructure failure in Egypt. The approach utilized in this study will equip policymakers with a valuable tool for effective decision-making and implementation in water pipeline works.

8. Conclusions

Rapid urbanization, occasioned by a growing population, has exerted significant pressure on WDS, making pipeline management more complex and challenging. To identify and analyze the critical factors contributing to the degradation of water distribution pipelines in Egypt, this study developed a novel failure decision-making model based on the PLS-SEM technique. The study leveraged previous research and insights from 125 water professionals, incorporating recent advancements in predictive modeling. Results indicated that “operational” factors were the most significant contributors to pipeline degradation, providing valuable direction for future infrastructure management strategies.

The implications of this study extend beyond academia. The identified factors and the developed model offer a practical framework for decision-makers in urban water management, particularly in prioritizing maintenance and resource allocation. This model has the potential to enhance water asset management practices in Egypt and other developing countries facing similar challenges of urbanization, aging infrastructure, and limited resources. It can support optimized maintenance schedules, extend infrastructure lifespan, and reduce costs related to unplanned failures.

While this research provided key insights, it also presents opportunities for future studies. Several relevant factors – such as pipe lifetime, pipe flow volume, number of junctions and connections, and surface cover conditions – could not be included in the current model due to data limitations. Future research should incorporate these variables to develop a more comprehensive failure analysis. Additionally, assessing the impact of climate change and

extreme weather events, disaggregating responses from various stakeholder groups, and utilizing a larger sample size could further enhance model robustness and applicability.

Funding

The authors express their gratitude to the Middle East University in Jordan for providing financial support to cover the publication fees associated with this research article.

Author contributions

The authors jointly contributed to the design and development of the research, analysis of the results, and writing of the manuscript.

Acknowledgements

The authors acknowledge the use of large language models, including ChatGPT and Grammarly to enhance the language and readability of this manuscript. These tools were employed to improve clarity and coherence while ensuring that the authors' original ideas and intellectual contributions remained intact. The authors take full responsibility for the content and interpretations presented in this paper.

Disclosure statement

The authors declare no conflict of interest.

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