ABC2: Journal of Architecture, Building, Construction, and Cities

Empowering research for Sustainable Development Goals, ABC2: Architecture, Building, Construction, and Cities is a fundamental manifesto to address these pressing issues, fostering dialogue and knowledge exchange among researchers, practitioners, and policymakers. Exploring sustainable design, resilient infrastructure, advanced construction methods, and equitable urban development, ABC2 aims to empower the global community to create adaptive, inclusive, and sustainable environments. The ABC2 focus on cutting-edge research, technological advancements, and transformative strategies is essential for navigating the future of our cities and communities.

Research Article

Analysing the Factors Contributing to Sewer Pipeline Failure under an Integrated Picture Fuzzy Environment with System Dynamic Modelling

Saeed Reza Mohandes[1], Sina Fadaie[2], Ehsan Aghdam[3], Sherif Abdelkhalek[3], Atul Kumar Singh[4*], Mohammad Mayouf[5], Tarek Zayed[3]

[1] Department of Civil Engineering and Management, School of Engineering, The University of Manchester, Manchester, United Kingdom
[2] College of Engineering and Physical Sciences, Aston University, Birmingham B4 7ET, United Kingdom
[3] Department of Building and Real Estate, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong
[4*] NICMAR Institute of Construction Management and Research, Delhi-NCR, Bahadurgarh, 124507, India
[5] College of the Built Environment (CEBE), Birmingham City University, Millennium Point, Birmingham B4 7XG, United Kingdom

Correspondence: atulkumarsingh22031996@gmail.com

Abstract

This study addresses the critical challenge of sewer pipeline failures, a problem of significant environmental and economic consequence. Despite the widespread impact, a research gap exists in quantitatively understanding the factors contributing to these failures, hindering the development of targeted mitigation strategies. The study introduces a novel amalgamation of Picture Fuzzy Set Theory with the Delphi technique (PFDM) and the System Dynamic Modeling (SDM) technique to fill this gap. Findings from content analysis reveal four main factors and twenty-three sub-factors, with environmental and structural elements emerging as predominant sub-factors to sewer pipeline failures. The proposed PFDM identifies eleven sub-factors as primary culprits, highlighting the critical role of factors such as pipe age, materials, damages from third parties, internal corrosion, and various types of cracks and holes. Importantly, sensitivity analysis demonstrates the robustness of these findings, showcasing consistency across diverse expert opinions. The SDM technique further underscores the interconnectedness of influential factors, emphasizing the need for targeted interventions. This research offers valuable insights for environmental and drainage decision-makers, helping them prioritize interventions to reduce sewer system failures and their associated environmental impacts, such as sewer overflow and exfiltration. By focusing on the identified critical factors and their complex relationships, the overall resilience and longevity of sewer pipelines will be enhanced.

Received: 30/11/2025
Revised: 23/12/2025
Accepted: 25/12/2025
Published: 31/12/2025

Volume: 2025
Issue: 02
Pages: 47-72

Keywords: Sewer pipeline; Fuzzy Set Theory (FST); Delphi Method; System Dynamics Modelling; Drainage networks; Sustainable infrastructure.

Highlights

- Quantifies key drivers of sewer pipeline failures using an integrated PFDM–SDM approach.
- Identifies 11 critical sub-factors, with pipe age, material, corrosion, and cracks most influential.
- Provides robust, decision-oriented insights to prioritize interventions and improve sewer resilience.

1 Introduction

The sewer network is an integral component of society's overall infrastructure due to its crucial role in managing the collection and transport of sewage, thereby hindering residents from exposure to hazardous pollutants (Najafi & Gokhale, 2005; Li, et al., 2019). It is widely accepted that sewer pipeline failure bears huge financial, social and environmental burdens (Balekelayi & Tesfamariam, 2019; Caradot, et al., 2018). Population growth and new environmental standards necessitate regular inspection and maintenance of sewer networks due to their susceptibility to deterioration and failure (Malek Mohammadi, et al., 2020). It is noteworthy that deterioration of a sewer pipeline is a continuous process, which consequently causes pipelines failure (Mohandes, et al., 2022). This deterioration can be attributed to a myriad of factors, including but not limited to physical, chemical, biological, and operational factors cause deterioration of a sewer network, which poses huge financial, social and environmental burdens (Chughtai & Zayed, 2007; Anbari, et al., 2017; Li, et al., 2019; Yin, et al., 2020; Hansen, et al., 2021). Therefore, determining the contributing factors to the sewer network deterioration and developing predictive models of sewer network's conditions are of great importance.

Predicting the conditions of a sewer network has attracted researchers' due to several reasons such as: (1) facilitating strategic planning for their inspection, maintenance and rehabilitation (Malek Mohammadi, et al., 2020; Egger, et al., 2013) (2) suppressing the financial costs of pipelines' maintenance (Zayed and Abdelkhalek, 2023; (Egger, et al., 2013) (3) hindering the propagation of contaminants from deteriorated pipelines and posing health and environmental hazards (Rutsch, et al., 2008; Egger, et al., 2013), and (4) preventing flooding due to the collapsed pipes (Saegrov, 2005; Egger, et al., 2013). The complexity of the deterioration process and the interconnected relationships among various parameters compound the challenge of accurately predicting the conditions of a sewer network (Owolabi et al., 2022). On the other hand, these profound issues motivate researchers to employ multiple predictive models, including deterministic models, statistical methods, and AI-based models (Carvalho, et al., 2018; Kleiner & Rajani, 2001).

Modelling the deterioration and failure of pipelines aims to forecast the condition of the pipelines and their future performance regarding influential factors (Balekelayi & Tesfamariam, 2019). Several models have been proposed to correlate the deterioration factors with the pipeline condition (Hawari, et al., 2020). Deterioration models are generally classified into three groups: (a) physical-based models, (b) statistical-based models, and (c) Artificial Intelligence (AI)-based models (Tran, 2007). Each of these models is explained in the following section.

Physical models establish a deterministic correlation between the parameters and the deterioration condition of the pipeline. Applying physical models to predict the conditions of a sewer pipeline requires detailed information regarding the properties of the pipeline network, operational conditions, and environmental factors, followed by an accurate analysis of the relationships between them (Rifaai, et al., 2022). Due to the intrinsic complexity of the interactions between several parameters, analysing the deterministic behaviour of the sewer pipeline network under different conditions in the large scale is not feasible (Kleiner & Rajani, 2001; Ana & Bauwens, 2010). Moreover, the deterministic models did not consider the inherent randomness or stochasticity of the pipelines' system (Malek Mohammadi, et al., 2020).

Statistical methods build a probabilistic relationship between the current parameters of pipelines as input and future conditions as output (Egger, et al., 2013; Ana & Bauwens, 2010). Due to their consideration of the inherent uncertainties of the system, statistical models are more appropriate for determining the condition of sewer pipelines and have been extensively adopted for engineering purposes (Henley & Kumamoto, 1992; Kuzin & Adams, 2005; Egger, et al., 2013). Statistical models can be divide into several categories, such as regression models, Markov and semi-Markov models, multiple discriminant analysis, evidential reasoning, cohort survival model and survival function (Hawari, et al., 2020; Malek Mohammadi, et al., 2020).

In their study, (Bakry, et al., 2016) applied multiple linear regression model to Closed-Circuit Television (CCTV) data to establish probabilistic relationship between the structural and operational conditions of a pipe and various factors, including the pipe's diameter, material, depth, and average daily traffic. In a different approach, (Salman & Salem, 2012) employed three statistical methods: ordinal regression, multinomial logistic regression, and binary logistic regression models, to predict the failure values of sewer pipeline sections. (Ariaratnam, et al., 2001) identified age, diameter, and type of the sewer as significant factors in determining the probability of deterioration in a pipeline. Conversely, (Davies, et al., 2001) identified several significant parameters affecting the structural deterioration of rigid pipelines. However, they found factors such as root penetration, history of burst water mains, and property age to be insignificant.

(Mohammadi, et al., 2019) developed a binary logistic regression model incorporating physical and environmental factors to predict the sanitary pipes' condition as either poor or good. They identified pipe age, material, diameter, length, and water table as the primary parameters influencing sewer pipeline condition. Notably, operational parameters were not considered in their model. (Chughtai & Zayed, 2007; Chughtai & Zayed, 2008) utilized multiple regression techniques to predict the condition of sewer pipes constructed from various materials. To provide a more comprehensive understanding of the pipes' conditions, in addition to the straightforward linear regression models, other regression models, such as exponential regression models, were also employed (Wirahadikusumah, et al., 2001; Micevski, et al., 2002; Baik, et al., 2006; Le Gat, 2008; Ana & Bauwens, 2010). The advantages of statistical models lie in their simplicity and consideration of the probabilistic nature of pipeline behaviour. Conversely, the disadvantages include sensitivity to noisy data, subjectivity in assigning condition ratings to pipes, and challenges in validating hypotheses, such as assuming standard normal distribution behaviour of measurement errors (Tran, 2007).

Recent studies have made significant contributions to this area. For instance, Salihu et al. (2023) developed an AI-based deterioration model that integrates unsupervised multilinear regression with Weibull analysis, effectively assessing the longevity of sewer pipes through CCTV data (Amini, 2023). In line with these efforts, El Morer et al. (2024) evaluated various degradation models, emphasizing the trade-off between model accuracy and explainability, which is critical for effective planning of CCTV inspections. Similarly, Kumar et al. (2024) applied machine learning algorithms to predict sewer pipe failure, showcasing the growing role of AI in modeling deterioration in infrastructure systems. Recent advances in deep learning techniques, such as convolutional neural networks (CNN), have also shown promise in the automated detection and classification of defects, further enhancing prediction accuracy and real-time monitoring capabilities.

The essence of AI-based models is the development of algorithms that can learn from past data and recognize patterns to predict future system behaviour based on current observations (Hawari, et al., 2020). Consequently, these models are referred to as data-driven models and typically demand a substantial volume of data (Scheidegger, et al., 2011). These algorithms may emulate the behaviour of the human nervous system, as seen in artificial neural networks. (Jiang, et al., 2016) predicted the initiation time of corrosion and the corrosion rate by training an Artificial Neural Network (ANN) on long-term data related to environmental factors. Their ANN model outperformed the multiple regression model. (Sousa, et al., 2014) evaluated and compared the performance of Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and logistic regression methods in predicting the behaviour of sewer pipelines. They concluded that ANNs exhibited the highest average performance. In another study, (Li, et al., 2019), employed three data-driven models – Multiple Linear Regression (MLR), Artificial Neural Network (ANN), and Adaptive Neuro Fuzzy Inference System (ANFIS) – to predict the initiation time and rate of corrosion for the same purpose.

According to the existing literature, the factors contributing to sewer pipeline failure are systematically identified and grouped into physical, operational, environmental, and structural defect categories, as presented in Table 1 along with their supporting references.

Table 1: Identified factors contributing to the failure of sewer pipelines.

Factors	Sub-factors	Code	Definition	Reference	Frequency
Physical Factors	Pipe length	SF1	Length of a sewer pipeline between two manholes	(Mohammadi, et al., 2019; Najafi & Kulandaivel, 2005; Baik, et al., 2006; Chughtai & Zayed, 2008; Ana & Bauwens, 2010; Davies, et al., 2001; Lubini & Fuamba, 2011; Syachrani, et al., 2011; Ennaouri & Fuamba, 2013; Syachrani, et al., 2013)(Harvey & McBean, 2014; El-Housni, et al., 2018; Cheng & Wang, 2018)	13
	Pipe diameter	SF2		(Mohammadi, et al., 2019; Najafi & Kulandaivel, 2005; Baur & Herz, 2002.; Baik, et al., 2006; Chughtai & Zayed, 2008; Ana & Bauwens, 2010; Lubini & Fuamba, 2011; Syachrani, et al., 2011; Ennaouri & Fuamba, 2013; Syachrani, et al., 2013)(Harvey & McBean, 2014; El-Housni, et al., 2018; Cheng & Wang, 2018)	13
	Pipe material	SF3	Concrete, vitrified clay, PVC, etc.	(Mohammadi, et al., 2019; Baur & Herz, 2002.; El-Housni, et al., 2018; Cheng & Wang, 2018; Najafi & Kulandaivel, 2005; Baik, et al., 2006; Chughtai & Zayed, 2008; Younis & Knight, 2010; Lubini & Fuamba, 2011; Ennaouri & Fuamba, 2013) (Ennaouri & Fuamba, 2013; Syachrani, et al., 2013; Syachrani, et al., 2011)	12
	Pipe age	SF4	Pipeline's age, grouped on five years period.	(Mohammadi, et al., 2019; Baur & Herz, 2002.; Najafi & Kulandaivel, 2005; Baik, et al., 2006; Ana & Bauwens, 2010; Chughtai & Zayed, 2008; Lubini & Fuamba, 2011; Syachrani, et al., 2011; Ennaouri & Fuamba, 2013; Syachrani, et al., 2013) (Harvey & McBean, 2014; El-Housni, et al., 2018; Cheng & Wang, 2018)	14
Operational Factors	Maintenance and repair practices	SF5	Maintenance practices such as flushes, repairs, recuts, backups, degrease and cleanings improve the sewer pipes' conditions. Improper maintenance leads to accumulation of deposits and intrusion of roots causing corrosion and defect.	(Chughtai & Zayed, 2008; Kuliczkowska, 2015; Balekelayi & Tesfamariam, 2019)	3
	Blockages (due to manhole defects, vandalism, ...)	SF6	Blockages such as sediments significantly affect the structure of the sewer pipelines. On the other hand, blockages hinder the flow inside the pipe and cause hydraulic problems.	(Hawari, et al., 2020; Tran, 2007; Angkasuwansiri & Sinha, 2013; McDonald, et al., 2001; Okwori, et al., 2021)	5
	Flow velocity	SF7	Higher flow rate of the fluids inside the pipelines increases the corrosion of pipelines. On the other hand, low flow rate of the fluids leads to the accumulation of suspended particles inside the pipeline.	(Hawari, et al., 2020; Kuliczkowska, 2015; Angkasuwansiri & Sinha, 2013)	3
Environmental Factors	Ground water level	SF8	Corrosion rate of the pipelines is inversely related to the resistivity of the surrounding soil, which is affected by the soil water content, which depends on the groundwater level.	(Hawari, et al., 2020; Mohammadi, et al., 2019; Syachrani, et al., 2011; Ennaouri & Fuamba, 2013; Wirahadikusumah, et al., 2001; Angkasuwansiri & Sinha, 2013)	6

	Soil characteristics	SF9	Characteristics of the soil, surrounding the pipe, such as corrosiveness, volume change associated with the moisture change, organic content and solvents' content, significantly affect deterioration rate of the pipelines.	(Hawari, et al., 2020; Mohammadi, et al., 2019; Baik, et al., 2006; Davies, et al., 2001; Ennaouri & Fuamba, 2013; Micevski, et al., 2002)	6
	Bedding and backfill conditions	SF10	Improper and non-uniform bedding condition exerts high pressure on the pipe and accelerates failure of sewer pipeline.	(Hawari, et al., 2020; Chughtai & Zayed, 2008; Davies, et al., 2001; Jiang, et al., 2016; Wirahadikusumah, et al., 2001; Angkasuwansiri & Sinha, 2013)	6
	Traffic volume and road type	SF11	Traffic volume exerts an extensive load on its pavement, which is transferred to the buried pipelines and may affect their structure. Moreover, high traffic load may cause ground displacement, which may disrupt the service of the pipes.	(Davies, et al., 2001; Jiang, et al., 2016; Hansen, et al., 2021)	3
	Land use	SF12	Different land uses and populations such as residential, industrial or agricultural, have different surfaces such as asphalt pavement, concrete or unpaved. Moreover, different activities are conducted on them, therefore, they exert different loads on the buried pipes.	(Hawari, et al., 2020; Hansen, et al., 2021; Angkasuwansiri & Sinha, 2013; Okwori, et al., 2021; Harvey & McBean, 2014)	5
	Ground movement	SF13	Ground movement and displacement caused by extra loadings such as earthquake, land slide, traffic, exert higher stresses on the pipelines in their vicinity.	(Hawari, et al., 2020; Davies, et al., 2001; Jiang, et al., 2016)	3
	Damages caused by third parties (e.g., contractors)	SF14	Damages such as cracks exerted during construction or bedding disturbance during excavations may cause structural failure over time.	(Tran, 2007; Angkasuwansiri & Sinha, 2013; Hou, et al., 2015; Tanoli, et al., 2019)	4
	Infiltration/ exfiltration	SF15	Infiltration of water through soil, may wash out particles of the surrounding soil and reduce its supporting the pipeline followed by pipeline's collapse. On the other hand, the groundwater's constituents such as salts or some corrosive compounds may lead to accumulation of deposits, encrustation and corrosion of pipelines. Exfiltration is the leakage of the pipe's flow from the failed joints or cracks on the pipe's wall.	(Hawari, et al., 2020; Mohmoodian, 2013; Hansen, et al., 2021; Angkasuwansiri & Sinha, 2013; Liu, et al., 2021)	5
	Root interference	SF16	Growing roots of the trees, that enter the pipes lead to their corrosion. Roots lead to the accumulation of debris and pipe blockages.	(Kuliczkowska, 2015; Kuliczkowska, 2016; Tran, 2007; Davies, et al., 2001; Li, et al., 2019)	5
	Climate conditions (temperature, precipitation, humidity, etc.)	SF17	Temperature variations may cause soil movement followed by increasing stress on the pipes and breaking them. It may cause expansion or contraction of the pipe material followed by cracks, too.	(Kerwin & Adey, 2020; Li, et al., 2019; Jiang, et al., 2016; Angkasuwansiri & Sinha, 2013)	4

			Higher soil humidity due to precipitation accelerates redox reactions followed by corrosion of the pipes.		
	Debris	SF18	Debris or deposits of materials in the sewer pipes specially in their ending sections leads to emission of SO2 followed by the pipe's corrosion. Deposits may sedimented in the bottom of the initial sections of the pipelines due to the low velocity of the flow. Solid deposits such as sediments obstruct the flow inside the pipe and restrict the hydraulic functions of the pipe.	(Davies, et al., 2001; Kuliczkowska, 2015; Tran, 2007; Li, et al., 2019; McDonald, et al., 2001)	5
Structural Defect	Displacement of pipes	SF19	Horizontal and vertical displacements of the pipelines may occur due to the ground motions, excavations and dewatering in the vicinity of the pipelines.	(Li, et al., 2003; Tan & Lu, 2018; Alarifi, et al., 2021)	3
	Internal corrosion	SF20	Corrosion in the sewer pipelines generally happens in their initial sections due to the deposits or in their end sections due to emission of H_2S and the activity of microorganisms and other corrosive compounds in the industrial wastewaters. Corrosion makes the pipe thinner and vulnerable to structural failure and leakage.	(Kuliczkowska, 2015; Kuliczkowska, 2016; Kerwin & Adey, 2020; Tran, 2007; Angkasuwansiri & Sinha, 2013)	5
	Cracks (Longitudinal, circumferential and multiple cracks) and holes	SF21	Longitudinal cracks in the sewer pipelines happen due to the structural overloading, flawed calculations during design insufficient capacity and embedding of the pipes and corrosion. Insufficient bedding of the pipes and movement of unstable soil under the pipe may cause circumferential cracks. Multiple cracks may occur when heavy stuff hits the pipe. Nonuniform forces and the lower capacity of the pipe, turn the cracks into fractures and will lead to pipe's failure.	(Kuliczkowska, 2015; Kuliczkowska, 2016; Davies, et al., 2001; Kerwin & Adey, 2020; Han, et al., 2002; Li, et al., 2019)	6
	Defects in the joints of the pipe	SF22	Improper transportation or assembly of pipes may cause defects of bells and spigots of the pipe's wall. Faulty joints on the wall of the pipes lead to exfiltration of the flow out of the pipes. Joint failure followed by pipe leakage leads to supporting soil erosion and pipe's failure.	(Kuliczkowska, 2015; Kuliczkowska & Bąba, 2018; Angkasuwansiri & Sinha, 2013; Xu, et al., 2017)	4
	Deformation of the pipe	SF23	The change in the diameter of the flexible pipes due to the load from the surrounding soil or hydrostatic pressure or stones near the pipe cause deformation. Deformation beyond a certain limit cause failure of the flexible pipes.	(Kuliczkowska, 2015; Davies, et al., 2001; Tee, et al., 2014; Mohmoodian, 2013)	4

			On the other hand, cracks on the pipe and destabilization of the surrounding soil may deform the sewer pipes or cause their collapse.		

While substantial progress has been made in developing models for sewer system management, there remain discernible gaps in the existing body of knowledge. This paper aims to address these gaps by focusing on several objectives, including clarifying the vague distinction between the concepts of 'failure' and 'deterioration.' It should be noted that several factors can contribute to the deterioration of sewer pipelines before their ultimate failure. However, predicting the time of failure and assessing the contribution of each factor to it are essential for facilitating proactive maintenance procedures. Additionally, this paper comprehensively investigates the influential parameters on sewer pipeline failure, prioritizes these parameters, determines their respective weights, and addresses the uncertainty associated with factors causing failure. These objectives are central to the scope of this paper. In other words, despite a relatively high number of studies undertaken in the concerned area, there are two major shortcomings that exist in the body of relevant knowledge, as follows:

1. There has been a dearth of studies that consider the uncertainty associated with the factors contributing to the failure of sewer pipelines. In fact, as mentioned by (Mohandes, et al., 2022), the deterioration of sewer pipelines follows a function, which illustrates the fact that related factors lead to failure with varying degrees of importance rather than a crisp value. In fact, all the studies conducted so far have assigned a single value to the factors contributing to sewer deterioration, overlooking the fact that each factor actually contributes to deterioration within a range of importance or significance levels. To address this issue, our study employs an advanced type of Fuzzy Set Theory (FST) to capture the maximum level of uncertainty associated with the importance of these factors in leading to eventual failure. By combining Picture Fuzzy Set Theory (PFST) with the Delphi Method (PFDM), the importance levels of the factors leading to the sewer pipeline failure were computed.
2. The current body of literature lacks an examination of the complex interrelationships among the factors and sub-factors that lead to the failure of sewer pipelines (Salihu et al., 2022). In other words, no study has yet investigated the influences that sub-factors to sewer failure have on each other within a dynamic and complex environment. To prudently address this intricate problem, this study employs System Dynamics Modelling (SDM), resulting in the development of a complex cause-and-effect relationship diagram.

The shortcomings mentioned above have motivated the authors to develop a hybrid fuzzy-based framework to achieve the following objectives: (I) Identification of all the factors and the corresponding sub-factors leading to sewer pipeline failure, (II) Calculation of the importance levels of these identified factors and sub-factors while considering the associated uncertainty, (III) Illustration of the complex relationships among the factors and sub-factors contributing to sewer pipeline failure, and (IV) Presenting the most critical factors and sub-factors to help decision-makers choose advanced technologies that provide additional information about sewer conditions, beyond what existing technologies offer. Also, addressing the maintenance of sewer systems in relation to the critical factors accelerating pipeline failures.

2 Research Methodology

This study employs a hybrid methodological approach to accomplish the defined objectives. Fig. 1 depicts the phases and their corresponding steps. There are four phases within the research framework, each detailed as follows:

- PHASE I: Identification of factors by employing content analysis and pilot study.
- PHASE II: Determination of critical factors using the proposed PFDM.

- PHASE III: Uncovering the interrelationships through the utilization of SDM.
- PHASE IV: Validation through experts' interviews.

The phases mentioned above are expounded in the following sub-section.

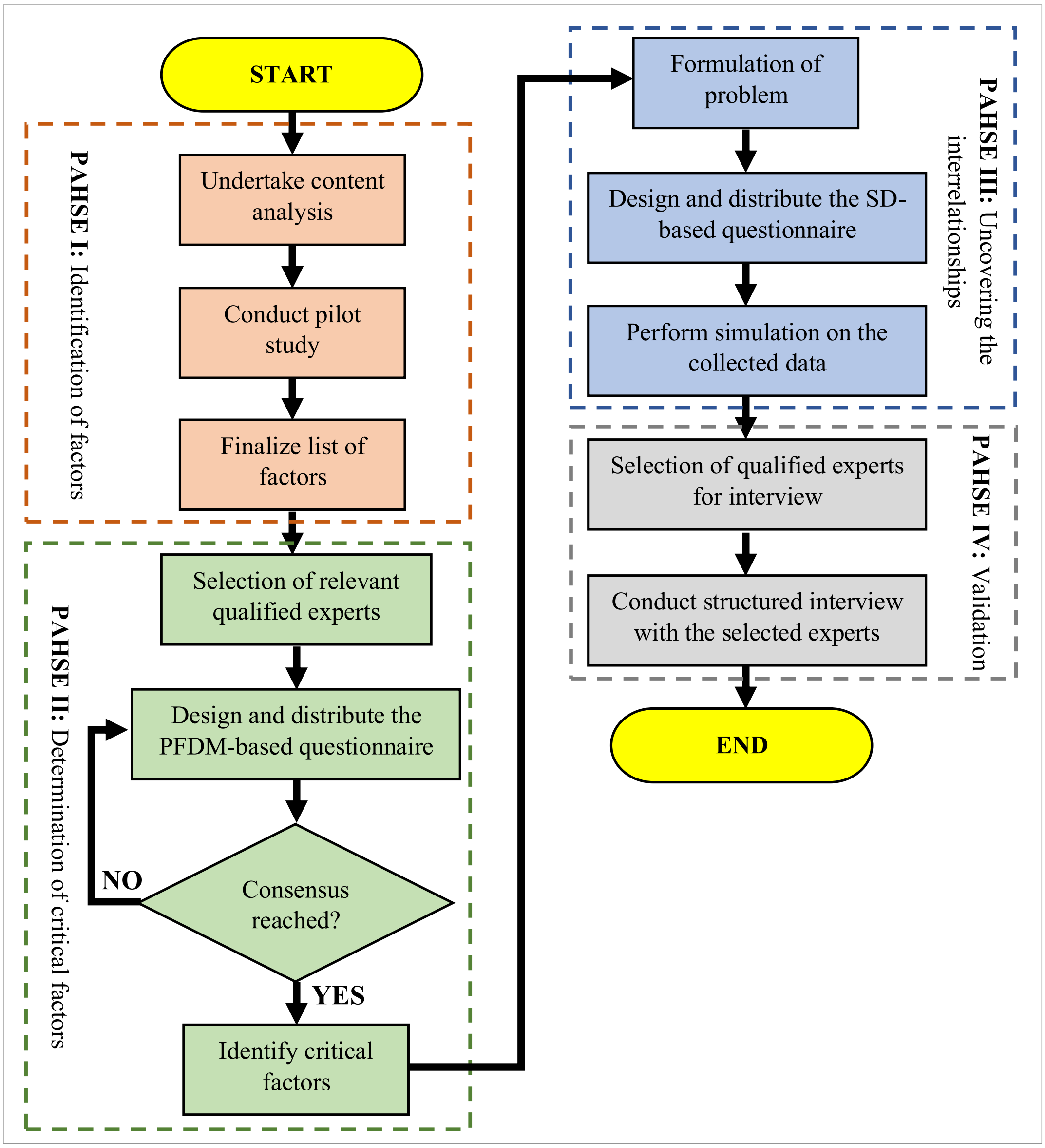


Figure 1: Research framework.

2.1 PHASE I: Identification of Factors

To fully identify the factors and sub-factors causing sewer pipeline failures, a content analysis of the relevant literature corpus, along with a pilot study carried out.

2.1.1 Content Analysis

The first step involved a systematic review, as described in Table 1. Initially, relevant keywords were searched in the Scopus database, followed by the application of specific criteria to exclude irrelevant papers. Relevant literature on sewer pipeline failure was found using a systematic search approach during the first data collection stage. The search keywords included terms such as "sewer pipeline failure," "sewer deterioration," "pipeline defects," "pipeline failure mechanisms," "sewer asset management," and "sewer infrastructure degradation." Boolean operators—e.g., AND, OR—were used to combine these keywords and hone the search results. The search mostly concentrated on subjects connected to the causes, mechanisms, and risk factors linked with sewer pipeline failures as well as maintenance and management practices for ageing sewer infrastructure. Preliminary scoping studies guided the choice of keywords and subjects with the goal of fully capturing the multidisciplinary nature of sewer pipeline failure, including structural, environmental, and operational elements.

Subsequently, the relevant papers were refined, and any irrelevant ones were removed in preparation for the content analysis. Once the relevant articles were identified, a detailed content analysis was conducted to identify the factors and sub-factors contributing to sewer pipeline failures. Through content analysis, one can determine the most important aspects and make valid inferences from visual, verbal, and/or written communication messages, whether quantitatively or qualitatively, regarding the nature of the project and the problems addressed in the research (Chan, et al., 2009; Krippendorff, 2013). By employing the content analysis technique, the necessary information can be effectively gathered and organized, while also allowing for a thorough examination of the patterns present in the documents (Krippendorff, 2013). Qualitative content analysis primarily focuses on categorizing data into different groups, whereas quantitative content analysis involves determining numerical values for the categorized data, such as frequencies, rankings, and ratings. This is achieved by counting the number of times a particular topic is mentioned (Chan, et al., 2009). In built environment research, the use of content analysis offers a level of flexibility and adaptability that is particularly beneficial in interdisciplinary research, a common characteristic of built environment studies. It can be tailored to suit various research objectives and can be used in conjunction with other research methods, such as surveys or interviews, to provide a more holistic understanding of the subject matter (Bhagwat and Delhi, 2022).

The present study combines both quantitative and qualitative content analysis to accomplish the defined objectives. Firstly, each published paper was scrutinized to classify the factors into their corresponding sub-factors. When a sub-factor was mentioned in a particular paper, the corresponding factor was noted next to it. At the end of this stage, a detailed list of factors and sub-factors was extracted from the literature. Following this, the number of times each factor or sub-factor was mentioned in the corpus of literature was carefully recorded. Accordingly, if a sub-factor was mentioned less than three times, it was removed (the threshold for retaining the sub-factors was set at three). This process allowed for the omission of less important sub-factors that were mentioned infrequently in the literature and were not considered significant by scholars in the concerned area.

2.1.2 Pilot Study

In order to validate the factors and sub-factors identified from the corpus of literature, a pilot study was conducted, as outlined in Table 1 (Mohandes, et al., 2022). This involved conducting several online interviews with qualified experts. During these interviews, the experts were asked to review the classifications provided by the research team, assess the definitions of the factors presented to them, and suggest additions or removals of any factors or sub-factors they deemed unimportant in relation to the failure of sewer pipelines. Table 1 illustrates the list of factors and their corresponding sub-factors contributing to sewer pipeline failures, which represents the output of Phase I.

2.2 PHASE II: Determination of Critical Factors

To come up with a prudent decision on the determination of critical factors leading to the sewer pipeline failures, this study proposes a PFDM. To ensure readers gain a comprehensive understanding of the methodologies and concepts underpinning this framework, a brief explanation of the Picture Fuzzy Sets (PFSs) is firstly provided, followed by a detailed elaboration of the steps encompassed within the proposed PFDM.

2.2.1 Picture Fuzzy Sets

PFSs are, in fact, the extended versions of Fuzzy Sets (FSs) and Intuitionistic Fuzzy Sets (IFSs) (Cuong & Kreinovich, 2013; Simic, et al., 2021). PFS models certain events that cannot be processed using other sets, such as IFSs and FSs (Cuong & Kreinovich, 2013). Therefore, its application to the description of ambiguous information is more accurate and realistic compared to using either FS or IFS (Simic, et al., 2021; Liu, et al., 2022). To make it more explicit, the utilization of PFS is applicable in conditions where the viewpoints of decision-makers encompass multiple response types: yes, abstain, no, and refusal (Simic, et al., 2021). Similarly, it has been noted that PFS is more effective in measuring concepts, objects, ideas, and other entities compared to other types of fuzzy sets. For instance, when dealing with the problem of locating a vehicle shredding facility, PFS proves to be a valuable tool for addressing information uncertainty.

In the context of sewer pipeline failure, Picture Fuzzy Sets can be employed to assess expert opinions on critical failure factors (e.g., pipe material degradation, joint displacement, and soil movement). For instance, when evaluating the risk of failure due to pipe material aging, the collected experts' responses can be expressed as varying degrees of importance: the respective factor contributes to failure (positive membership), the respective factor is neutral towards the failure (neutral membership), the respective factor does not lead to the pipeline failure (negative membership). By capturing this range of responses, PFSs enable a more nuanced and comprehensive representation of the uncertainty inherent in infrastructure assessments (Farmani et al., 2017; Yamijala et al., 2009). PFS is characterized by three functions: the degree of negative membership, the degree of neutral membership, and the degree of positive membership. PFSs are capable of effectively describing the uncertain information typically encountered in this emerging facility location problem. They also perform well in mitigating incidents of information loss. To facilitate the readers' understanding, the following preliminaries of PFS are provided in light of the above explanations.

Preliminary 1. A PFS on a S ˜p of the universe of discourse U can be denoted as:

$$\tilde{S}_p = \left\{< u, \left(\alpha_{\tilde{S}_p}(u), \beta_{\tilde{S}_p}(u), \gamma_{\tilde{S}_p}(u)\right) > | u \in U\right\} \qquad (1)$$

where

$$\alpha_{\tilde{S}_p}(u), \beta_{\tilde{S}_p}(u), and\ \gamma_{\tilde{S}_p}(u): U \rightarrow [0,1] \qquad (2)$$

and

$$0 \leq \alpha_{\tilde{S}_p}(u), \beta_{\tilde{S}_p}(u), and\ \gamma_{\tilde{S}_p}(u) \leq 0 \qquad (3)$$

In the above-mentioned equations, $\alpha_{\tilde{S}_p}(u), \beta_{\tilde{S}_p}(u), and\ \gamma_{\tilde{S}_p}(u)$ are respectively membership's degree, non-membership's degree, and indeterminacy's degree of u to $\tilde{S}_p$. In this regard, the refusal degree is denoted as below:

$$RD_{\tilde{S}_p} = 1 - (\alpha_{\tilde{S}_p}(u) + \beta_{\tilde{S}_p}(u) + \gamma_{\tilde{S}_p}(u)) \qquad (4)$$

Preliminary 2. The four basic operators of PFSs are elaborated as follows:

$$\tilde{S}_p \oplus \tilde{T}_p = \left\{\alpha_{\tilde{S}_p} + \alpha_{\tilde{T}_p} - \alpha_{\tilde{S}_p}\alpha_{\tilde{T}_p}, \beta_{\tilde{S}_p}\beta_{\tilde{T}_p}, \gamma_{\tilde{S}_p}\gamma_{\tilde{T}_p}\right\} \qquad (5)$$

$$\tilde{S}_p \otimes \tilde{T}_p = \left\{\alpha_{\tilde{S}_p}\alpha_{\tilde{T}_p}, \beta_{\tilde{S}_p}\beta_{\tilde{T}_p}, \gamma_{\tilde{S}_p} + \gamma_{\tilde{T}_p} - \gamma_{\tilde{S}_p}\gamma_{\tilde{T}_p}\right\} \qquad (6)$$

$$\psi.\tilde{S}_p = \left\{\left(1 - \left(1 - \alpha_{\tilde{S}_p}\right)^{\psi}, \beta_{\tilde{S}_p}, \gamma_{\tilde{S}_p}\right)\right\}, for\ \psi > 0 \qquad (7)$$

$$\tilde{S}_p{}^{\psi} = \left\{\alpha_{\tilde{S}_p}, \beta_{\tilde{S}_p}\left(1 - \left(1 - \gamma_{\tilde{S}_p}\right)^{\psi}\right)\right\}, for\ \psi > 0 \qquad (8)$$

2.2.2 Fuzzy Delphi Method

In the context of qualitative research, the Delphi method is widely used as an instrument for collecting and analysing data. This method systematically and interactively gathers the opinions of a selected panel of experts regarding their individual viewpoints on a specific issue (Mohandes, et al., 2022; Mohandes, et al., 2022; Tabatabaee, et al., 2022). Typically, a series of questionnaires is employed in this method, which can be distributed via email, through the World Wide Web, or in person to gather the necessary data. Through these questionnaires, experts anonymously provide their opinions in sequential rounds until the researcher achieves maximum consensus without infringing upon the participants' autonomy. The researcher selects experts based on predefined criteria, administers questionnaires, collects and analyses responses, and finally draws conclusions. If necessary, the facilitator may analyse the results and provide feedback using statistical methods.

Considering the points mentioned above, a review of the literature reveals a significant body of studies that have utilized the Delphi method to elicit, refine, and leverage expert opinions on various subjects (Cortés, et al., 2012; Kermanshachi, et al., 2020; Mohandes, et al., 2022). In numerous studies, this method has been adopted to mitigate the negative effects of group interactions and to ensure equal opportunities for all participants to express their views and participate in decision-making processes (Gupta & Clarke, 1996). However, a number of scholars have mentioned two drawbacks of the conventional Delphi method: 1) the low final convergence of the opinions, and 2) ineffectiveness of the procedures of the method in practice. The reason is the iterative inquiries that are required for the achievement of a consensus (Mahdiyar, et al., 2018; Durdyev, et al., 2022). In addition, in Delphi-based studies, participants express their opinions verbally, which several scholars have identified as a challenge. This is because verbal expressions often do not fully capture a person's true thoughts, and, as a result, participants' mental latencies are often concealed in this process. To overcome this limitation, the Fuzzy Set Theory (FST) was proposed to effectively handle issues related to the ambiguity, subjectivity, and fuzziness of individuals' thoughts. FST quantifies the linguistic aspects of collected data and reveals preferences expressed during decision-making sessions (Tabatabaee, et al., 2022).

As mentioned earlier, FST extends the conventional set theory by assigning membership grades to elements within a set, ranging from 0 (non-membership) to 1 (full membership) (Mohandes & Zhang, 2019). While the introduction of FST, including triangular fuzzy numbers, trapezoidal numbers, pentagonal fuzzy numbers, etc., into the traditional Delphi technique has addressed the previously mentioned issues, it still falls short of fully capturing the uncertainty of factors considered in a problem and the subjectivity of participating experts. This limitation arises from the fact that these fuzzy sets, designed to handle the uncertainty of a phenomenon, only incorporate membership values. They do not account for other complex forms of uncertainty associated with a problem. Consequently, this study introduces a novel approach, the combination of PFS and the Delphi technique (PFDM), for the first time. The proposed PFDM can comprehensively capture the uncertainty associated with a problem by considering not only the membership values of a factor under investigation but also its non-membership and indeterminacy values. As such, the following steps were undertaken to execute the PFDM and rank the identified factors contributing to sewer pipeline failures, subsequently determining the most critical ones.

<u>Step 1. Selection of relevant qualified experts:</u>

According to (Okoli & Pawlowski, 2004), a minimum of 10 people is normally suitable for each expert panel. For the purpose of the present study, two strict criteria for the selection of qualified experts with rich experience in Hong Kong were considered. First, they had to have at least three years of professional experience in dealing with the rehabilitation, repairment, and replacements of sewer networks in Hong Kong (either as researchers or practitioners). Second, they had to hold at least bachelor’s degree related to the area of Civil Engineering and Management. Following the specified requirements, 15 experts were selected to participate in PFDM, whose profiles are illustrated in Table 2.

It is worth noting that though the choice of experts was guided by explicit standards about their academic credentials, professional background, and relevance to sewer pipeline infrastructure, the possibility of selection bias was acknowledged and actively handled. Efforts were made to guarantee variety among the expert panel to reduce prejudice. To prevent institutional bias, experts were chosen from various organisations, including academic institutions, private consulting firms, and public authorities. Furthermore, professionals with different vocational responsibilities were included from asset management, maintenance, design engineering, to field operations to capture a whole spectrum of viewpoints. That is to say, the panel was not dominated by any one organisation or professional speciality. Moreover, the invitation procedure was designed to prevent personal acquaintance prejudice by sending formal invitations depending on expertise qualifications rather than personal knowledge. During data processing, responses were ultimately anonymised to reduce possible impact from hierarchical or organisational ties. These steps were taken to improve the credibility and generalisability of the expert judgements acquired.

Table 2: Profile of the experts selected for PFDM.

Expert ID	Job/Position	Years of experience	Education	Degree	Participation			
					Pilot study	PFDM	SD	Validation
1	ACD	17	PhD	BD&CN	●	●	●	
2	END	8	Bachelor	CIVL		●	●	
3	END	3	Bachelor	CIVL		●		
4	END	14	Bachelor	CIVL	●	●	●	
5	END	3	Bachelor	CIVL	●	●	●	
6	END	12	Master	CIVL		●	●	
7	END	16	Bachelor	CIVL		●		
8	ACD	3	Master	CIVL	●	●	●	
9	END	17	Bachelor	CIVL		●		
10	END	15	Master	CIVL	●	●	●	
11	END	17	Bachelor	CIVL		●		
12	END	15	Bachelor	CIVL		●	●	
13	END	16	Bachelor	CIVL		●	●	
14	ACD	3	PhD	BD&CN		●	●	
15	ACD	3	PhD	BD&CN		●	●	
16	END	12	Bachelor	CIVL				●
17	END	14	Bachelor	CIVL				●
18	END	11	Bachelor	CIVL				●
19	ACD	18	Bachelor	CIVL				●

Note: ACD: Academician (Professor, Lecturer, Research Assistant, etc.); END: Engineer/designer; BD&CN: Building and Construction; CIVL: Civil engineering (e.g., Infrastructure, Structural, Hydraulic, Transportation, or Geotechnical Engineering).

Step 2. Designing the PFDM-based questionnaire:

First, the factors contributing to the failure of sewer pipelines were identified through a comprehensive literature review (as mentioned in the literature review section). Once the factors were identified, they were then presented to relative experts to have them pilot tested. Then, based on the modified list of factors, a structured questionnaire was prepared with the use of the linguistic variables given in Table 1, which ranged between two extremes of very low importance and very high importance, as recommended by the authors in (Mohandes, et al., 2022; Mohandes, et al., 2022). Next, the questionnaire was sent to fifteen selected experts to be filled out using the linguistic variables clearly defined. It should be noted that because of the implementation of the PFS in the current research, each fuzzy set contains three different values: the highest possible value, the most likely values, and the lowest possible one.

The present study attempts to use the benefits of the information technology by employing an online application to make the stage ready for information flow between the facilitator and the selected experts. It makes the processes simpler by accelerating the interactions with the participants. The objectives of the research and the method adopted to accomplish them were elaborated for the selected experts first via mail; then, after they decided to take part in this study, the facilitator answered their specific questions with more details during face-to-face meetings and/or telephone conversations. The experts' opinions were analysed and exposed to necessary processing and then taken into account in the succeeding rounds. In this way, the researchers attempted to provide a suitable ground for the exchange of views and, at the same time, preserve the participants' anonymity.

The resultant information in terms of the method, questionnaire, and the results of each round was integrated and presented in a definite place to be simply, fast, and effectively referred by the experts.

Step 3. Seeking consensus in the experts' responses:

After the participants filled out the questionnaires, it was time to determine if consensus could be elicited. To achieve this, the following two rules were considered, which were suggested by (Mohandes, et al., 2022); (a) A consensus was reached for a definite sub-factor if and only if the Standard Deviation to Mean Ratio (SDMR) for that sub-factor was lower than 30%, whereas the exact value of 30% or greater was translated to a poor consensus. In this case, the respective experts were required to make some adjustments on their responses in next round(s). Note that for each factor, SDMR was computed separately based on the filled questionnaires sent back by the participants. (b) The answers of an expert were deemed prudent if the respective Cronbach reliability test result was equal to or greater than the threshold of 0.7; otherwise, they were considered imprudent, which necessitated being done again. The Cronbach reliability test checks whether or not the responses of an expert are consistent.

Step 4. Identifying the critical factors:

When a consensus was reached among the experts, it became necessary to quantify the answers provided by them. The current study employs PFDM, which utilizes the PFSs to identify critical failures with the goal of quantifying the variables assigned to the determined factors. Consequently, the minimum, neutral, and maximum values of the experts' opinions were considered as the three terminal points of PFSs. The arithmetic mean is considered the membership degree of TFNs when deriving the statistically unbiased impact. Moreover, this helps users avoid the impacts of extreme values. Thus, the implementation of TFNs leads to further simplicity because it covers the opinions of all the participants in only one investigation (Tabatabaee, et al., 2022). After filling out the questionnaire, the research team began to quantify the linguistic variables assigned to each obstacle. To do this, Equations (9) and (10) were used to compute the aggregation of the experts' feedback for the 'j' failure factor.

$F_i(b) = (\alpha_b, \beta_b, \gamma_b)$, for $i = 1, 2, \dots, n$	(9)
$B(b) = (\alpha_B, \beta_B, \gamma_B) = (min\ \alpha_b, mean\ \beta_b, \max \gamma_b)$	(10)

Where $F_i(b)$ denotes the TFN response of the expert i for factor b, $B(b)$ denotes the aggregation of the responses of all of the participants for the factor b (where $min\ \alpha_b, mean\ \beta_B, \max\max \gamma_b$ stand for the minimum lower bound value assigned by the participants, the mean of the most probable value assigned by the participants based on the arithmetic mean, and the maximum upper bound value assigned by the participants, respectively. Then, the defuzzification process was executed on the responses aggregation in order to attain a crisp value as the significance of each sub-factor. Equation (11) defines the defuzzified value DEF_j, indicating the significance of a specific sub-factor denoted by $\tilde{S}_j$. Here, $\alpha_{\tilde{S}_j}$ serves as a scaling sub-factor, influencing the weighting of $\tilde{S}_j$, while $\gamma_{\tilde{S}_j}$ functions as a subtraction term, adjusting its impact. $\beta_{\tilde{S}_j}$ acts as a division sub-factor, modulating the contribution of $\tilde{S}_j$, with the division sub-factor halved. The resultant DFZ_j encapsulates the amalgamated effect of these parameters in a defuzzification process, providing a precise quantitative measure of the sub-factor's significance.

$DEF_j = \frac{1}{2}\left(1 + 2\alpha_{\tilde{S}_j} - \gamma_{\tilde{S}_j} - \frac{\beta_{\tilde{S}_j}}{2}\right)$	(11)

For the identification of the critical factors, as proposed by the authors in (Bouzon, et al., 2016), a threshold value is required to be computed using Equation (12) as follows:

$TS = \frac{\sum_{i=1}^{g} DEF_j}{g}$	(12)

where DEF_j signifies the defuzzified number of the aggregated responses for sub-factors b, and TS represents the threshold value. In case a particular sub-factor' defuzzuifed value is higher than the defined threshold value, the sub-factor is classified as a critical obstacle; otherwise, it is regarded as non-critical. Remember that, for the prioritization purposes, greater final weights of sub-factors (which is signified as DEF_j) show that the respective sub-factor is more critical. The parameter g represents the number of sub-factors identified in the research.

2.3 PHASE III: Uncovering the Interrelationships

To uncover the interrelationships among the critical factors, System Dynamic Modelling (SDM) was used in this study. As shown in Fig. 1, there are three steps involved in developing the SDM with following details:

Step 1. Initially, the problem at hand was formulated: In doing so, the deterioration process was investigated to identify its main components. Practically, a pipe deteriorates over its service life at a specific deterioration rate, which is influenced by several factors/sub-factors. Furthermore, the interrelations between these factors/sub-factors affect the impact of each factors/sub-factors on the deterioration rate, highlighting the need to determine such interrelations for simulation in the SDM. Step 2 was devoted to identifying these interrelations. These factors/sub-factors and their importance weights are shown in Table 3. The top-ranked sub-factors (i.e., 11 sub-factors based on PFDM) were used in this study to formulate the SDM.

It is worth underscoring that, within the scope of this study, deterioration refers to the progressive decline in the condition of sewer pipelines, whereas failure denotes the critical point at which a pipeline can no longer perform its intended function. This conceptual distinction plays a pivotal role in shaping the structure of the proposed model. The PFDM component is designed to assess the relative influence of various contributing factors on the deterioration process, while also capturing the inherent uncertainty in expert evaluations. In parallel, the SDM component models how these deteriorative influences accumulate and interact over time, ultimately leading to failure. By addressing both the gradual nature of deterioration and the tipping point of failure, this layered modelling approach offers a more refined basis for planning preventative interventions – supporting decision-makers in taking timely action before failure occurs.

Step 2. Design and distribute the SD-based questionnaire: Once the problem was properly formulated, the research team developed a questionnaire survey to uncover the interrelationships among the identified critical factors. To do this, selected qualified experts were required to determine the impact of factors on each other by indicating 'YES' or 'NO'.

Step 3. Build the SDM using the collected data: First, all deterioration factors were presented as dynamics variables (Figure 6). This allows to change their values during the simulation. For example, the 'age' factor obtains its value from the simulation time. Second, the interrelations between these factors were presented as grey and red links. A grey link represents single-direction relationship, whereas the red one represents bio-direction relationship. The impact of 'age' on the other factors was presented using grey links. The impact of other factors on 'age' was indirectly represented by linking these factors to the deterioration rate, as the pipe's end-of-life age is determined when a grade of 'updated condition' is assigned to the Finally, applying maintenance activities to a pipeline changes its current condition using the condition relationships.

2.4 PHASE IV: Validation

Further interviews with the qualified relevant stakeholders were undertaken. In doing so, four experts who had more than 10 years of relevant experience were selected for the interview. Notably, the interviews were carried out in online mode, due to the preferences of the interviewees. The interviewees were asked to exchange their views on the importance of the critical factors determined by PFDM, as well as the relationships that exist among the factors considered using SDM. It is notable that the average duration of the interviews held was roughly twenty-five minutes. On top of all that, the results obtained in this research were compared against the real-life cases in Hong Kong, by referring to the data collected through the Closed-Circuit Television (CCTV) inspections by the Drainage Services Department (DSD).

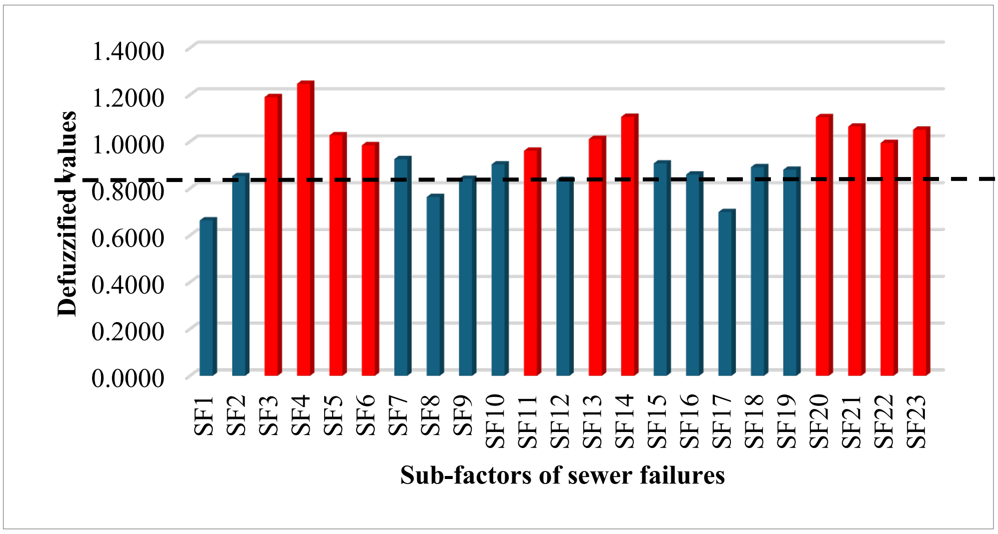
3 Results and Discussions

As discussed, in practical application, a pipe deteriorates over its service life at a specific rate. This rate is influenced by several factors. Furthermore, the complex interactions between these variables govern the extent to which each specific element contributes to the deterioration rate. This emphasizes the imperative to elucidate these intricate connections, essential for their incorporation into the System Dynamic Modelling (SDM) framework. To unravel the interrelationships among pivotal factors, the second phase of the study was exclusively focused on identifying of these interrelations. The outcomes of this endeavour, including the sub-factors themselves and their respective significance weights, are accurately presented in Table 3.

Table 3: Importance weights of the identified sub-factors.

CODE	Membership function (M)	Non-membership function (NM)	Indeterminacy value (IV)	Defuzzified (DEF)	Rank	SDMR (1st round)	SDMR (2nd round)
SF1	0.413	0.033	0.483	0.6633	23	18	18
SF2	0.537	0.037	0.350	0.8525	18	31	17
SF3	0.760	0.027	0.127	1.1900	2	27	27
SF4	0.800	0.027	0.093	1.2467	1	2	2
SF5	0.653	0.047	0.230	1.0267	7	13	13
SF6	0.623	0.030	0.263	0.9842	10	14	14
SF7	0.587	0.047	0.300	0.9250	12	16	16
SF8	0.480	0.047	0.410	0.7633	21	17	17
SF9	0.530	0.037	0.360	0.8408	19	29	29
SF10	0.570	0.030	0.320	0.9025	14	22	22
SF11	0.610	0.030	0.283	0.9608	11	7	7
SF12	0.530	0.043	0.367	0.8358	20	9	9
SF13	0.643	0.043	0.243	1.0108	8	3	3
SF14	0.703	0.030	0.180	1.1058	3	6	6
SF15	0.573	0.040	0.313	0.9067	13	9	9
SF16	0.543	0.030	0.353	0.8592	17	11	11
SF17	0.437	0.023	0.463	0.6992	22	15	15
SF18	0.563	0.050	0.320	0.8908	15	13	13
SF19	0.553	0.027	0.333	0.8800	16	27	27
SF20	0.703	0.030	0.183	1.1042	4	33	19
SF21	0.677	0.037	0.207	1.0642	5	22	22
SF22	0.630	0.037	0.253	0.9942	9	21	21
SF23	0.670	0.037	0.220	1.0508	6	28	28
Threshold							0.946
Cronbach Alpha (1st round)							0.7195
CronbachAlpha(2nd round)							0.7304

As can be seen, these Defuzzified (DEF) values represent a comprehensive evaluation of the importance of the 23 sub-factors, taking into account all viewpoints expressed in the incorporated studies. It is evident that all sub-factors have DEF values more than 0.6632. However, only seven sub-factors have DEF values greater than 1.0000, indicating their significant importance. According to the results of this analysis, SF4, SF3, SF14, and SF20 (pipe age, pipe materials, damages caused by third parties (e.g., contractors), and internal corrosion) are the most crucial sub-factors, while SF1, SF17, SF8, and SF12 (pipe length, climate conditions, ground water level, and land use) are considered the least important sub-factors to sewer pipeline deterioration.



Legend:
Blue colour bars: non-critical sub-factors
Red colour bars: Critical sub-factors
Dot line: The specified threshold value

Figure 2: Critical sub-factors contributing to sewer failure.

To facilitate comparative analysis, a bar chart illustrating all significant sub-factors that contribute to sewer failures is depicted in Fig. 2. The defuzzified value of 1.0000 serves as the designated threshold. In accordance with this threshold, factors deemed critical (above the threshold) and non-critical (below the threshold) are respectively depicted by red and blue bars. Furthermore, it is evident that SF4 (pipe age) and SF1 (pipe length) hold the status of the most and least important sub-factors, respectively, influencing the sewer pipeline deterioration process.

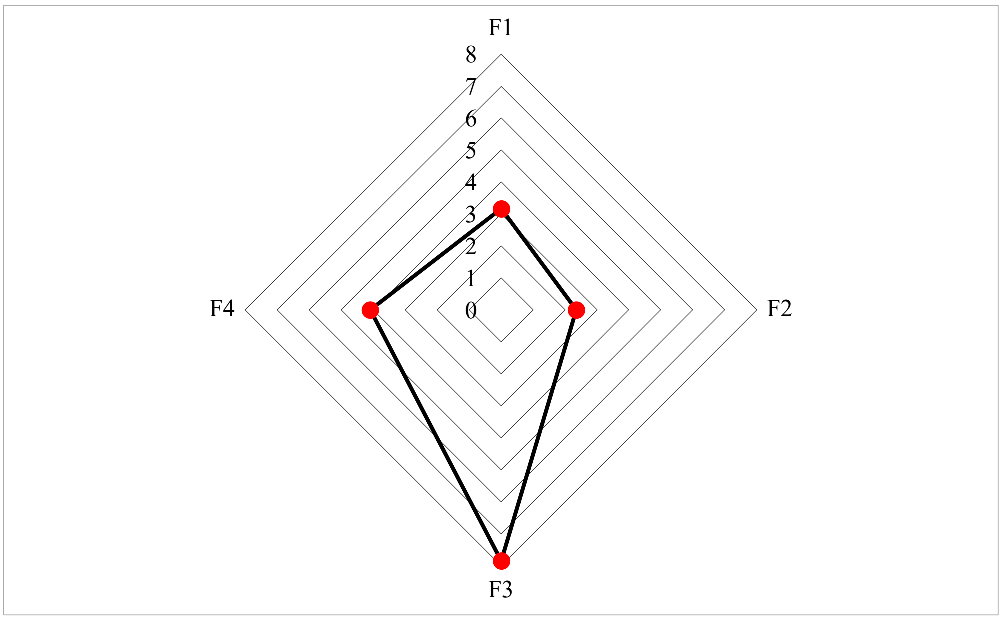


Figure 3: Importance weights of main factors contributing to sewer failure.

Following the literature review conducted, four main factors contributing to the sewer failure are defined: physical, operational, environmental, and structural factors. Fig. 3 presents all main factors along with their relevant importance weights in a radar chart. It is evident that F3 and F2 are related to the most and the least important main factors, respectively.

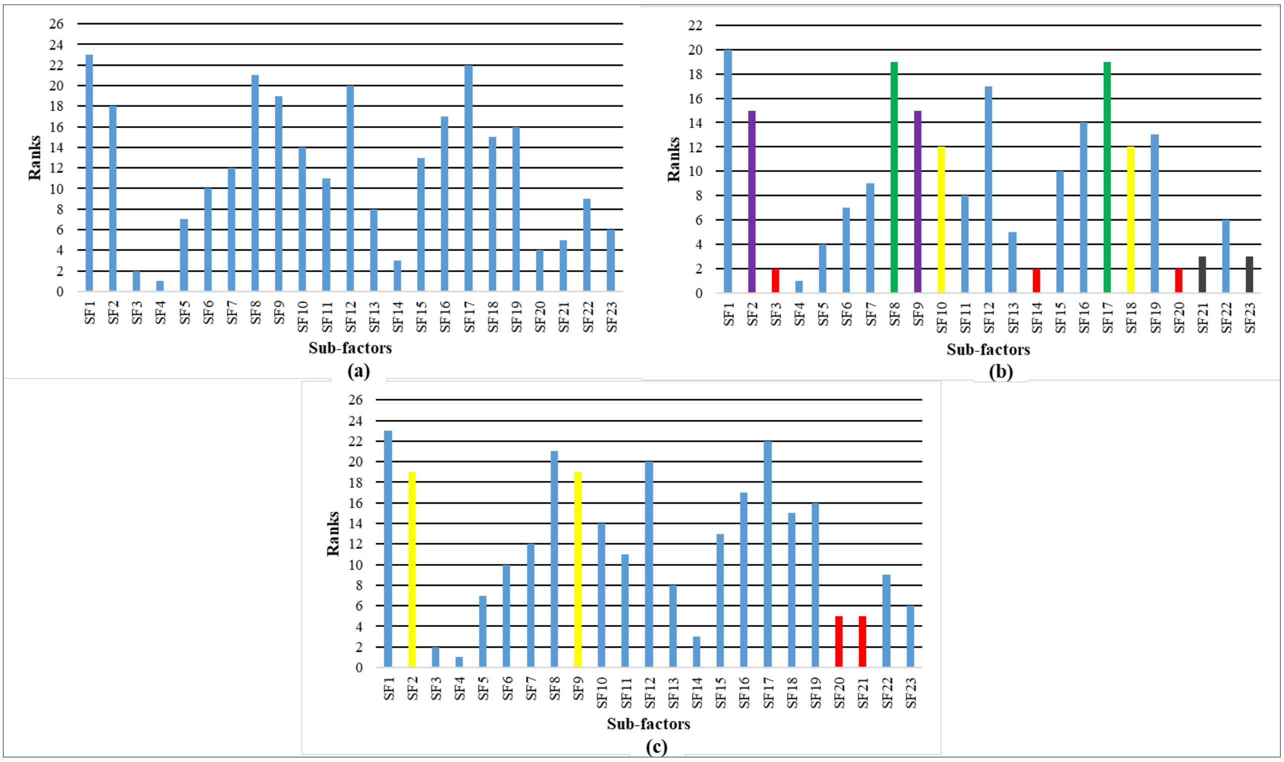


Figure 4: Diversifications of the rankings obtained from the application of different methods: (a) the proposed PFDM, (b) traditional Delphi technique, and (c) triangular fuzzy Delphi method.

Fig. 4 represents the diversifications of the rankings captured employing different approaches: the proposed PFDM, traditional Delphi technique, and triangular fuzzy Delphi method. While the Triangular Fuzzy Delphi method yields more appropriate results compared to the traditional Delphi technique, neither of these approaches can fully capture the uncertainty associated with a given problem. This limitation arises from their inability to comprehensively encompass the uncertainty inherent in the factors considered within a problem, as well as the subjectivity introduced by the participation of experts in the study. The PFDM proposed in this study, however, offers a solution to this issue. By incorporating not only the membership values of the factors under investigation but also their non-membership and indeterminacy values, this approach enables a comprehensive understanding of the uncertainty tied to a problem. Consequently, the proposed PFDM effectively prioritizes the identified factors contributing to sewer pipeline failure and facilitates the identification of the most crucial ones.

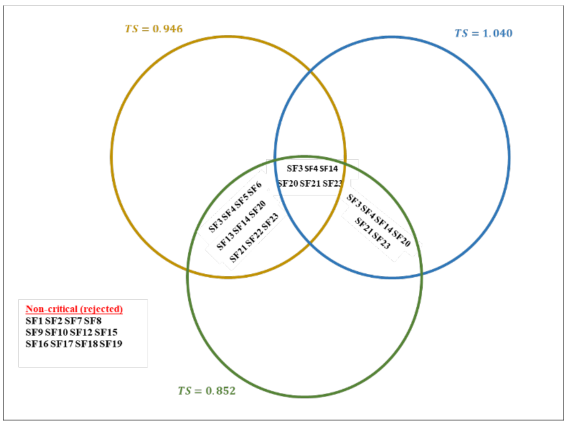


Figure 5: Sensitivity analysis.

To determine the final list of sub-factors, a sensitivity analysis was conducted, considering a defuzzified value of 1.0000 as the designated threshold. It should be noted that the threshold value is extremely crucial, as it determines whether a factor is considered a contributing factor to sewer failure or not. As seen, 13 sub-factors were classified as non-critical (rejected), while 11 sub-factors were identified as parameters contributing to the deterioration of the sewer.

Over time, sewer pipes experience deterioration due to several quantifiable factors, such as increased root intrusion and roughening of the interior pipe surface. Quantitative studies have shown that pipe roughness is directly associated with frictional resistance, potentially reducing flow capacity by up to 30% and accelerating hydraulic performance loss (Fugledalen et al., 2023; Kaddoura, K., & Atherton, 2021). Sewer pipe deterioration rates are also significantly influenced by the pipe material. For instance, concrete pipes manufactured under controlled factory conditions show around 20–25% higher structural integrity compared to brick pipes produced onsite under variable workmanship conditions (Zeng et al., 2023). Reinforced concrete pipes, strengthened with steel reinforcement, have demonstrated up to 50% higher resistance to structural deterioration compared to non-reinforced alternatives. Furthermore, performance comparisons reveal that vitrified clay pipes outperform asbestos cement and reinforced concrete pipes under similar operational conditions, achieving 10–15% longer service life in empirical evaluations.

Another critical factor is the defectiveness of joints, where infiltration rates can increase by up to 35% due to defective seals, leading to soil entry and sewer system destabilization (Goodarzi & Vazirian, 2024). Surface loads also play a measurable role in sewer deterioration. Pipes subjected to heavy traffic loads experience stress levels that can exceed design limits by approximately 40%, with urban pipes showing a failure probability that is 2.5 times higher than those in rural settings (Farmani et al., 2017). Sudden excessive loads from construction activities, earthquakes, or landslides, as well as repetitive cyclic loads from daily traffic, have been statistically linked to early pipe failures, highlighting the need for stress analysis in high-risk zones.

Additionally, third-party interferences, such as excavation and mechanical cleaning, contribute to pipeline degradation, with older pipes being 1.8 times more susceptible to such damages compared to newer installations (Kleiner & Rajani, 2000). Improper maintenance activities have also been linked to increased operational failures, with studies showing a 25–30% higher incidence of blockages and backups in poorly maintained systems (Salihu et al., 2023). Environmental stresses like basement flooding, hydraulic overloads, and sewer overflows present further quantifiable risks, with overflow events correlating to a 20% rise in public health and environmental hazards. Targeted maintenance strategies, particularly in areas with historically high failure or blockage rates, could reduce collapse incidents by up to 15%, supporting proactive, data-driven sewer management.

Too much sediments or root intrusion cases generally result in external corrosion, which causes the sewer pipes to experience blockage (Davies, et al., 2001; Kuliczkowska, 2015; Kuliczkowska, 2016; Salihu, et al., 2022). Moreover, abrasion (internal corrosion of pipes), which is induced by an abrupt rise in the flow of sewage inside the pipes, causes the pipeline to progressively experience various forms of cracks and fractures. Thus, in turn, results in partial or full blockage. If a pipeline is exposed to full blockages, it may lead to the collapse of the pipeline. Some ground movements induced by, for instance, the trench excavation considerably increase the stress upon the backfill of constructed sewers, which results in the failure of the constructed pipes. Furthermore, factors such as sulphide, hydrogen, and micro-organisms cause internal corrosion of the sewer pipelines. Such factors typically lower the sewers load capacity, which may result in secondary defects, e.g., deformation, fracture and crack, leak-tightness, and collapse. They could also raise the sewer wall roughness, thereby decreasing the flow capacity.

Crack is another sub-factor that can seriously cause the collapse of the sewer pipelines. A crack may be the result of various factors, for instance, the third-parties' interference, age of pipes, blockage, utilization of heavy construction equipment, abrasion, and roots intrusion (Kuliczkowska, 2016; Salihu, et al., 2022). As the pipeline gets older and older, it becomes prone to cavities and then cracks. Additionally, cracks or fractures may develop because of the raptures that occur to them due to the miscarriage of maintenance activities. Abrasion, which refers to the internal corrosion, is another remarkable factor that deteriorates the cracks developed along the pipelines. This mainly take place due to the presence of blockage in the system, which may appear due to sediments or root intrusion. In such condition, the sewage flow does not pass easily through the pipes, hence increasing considerably the flow velocity. This causes the internal surface of pipes to get abraded and, consequently, widens the already-existing cracks or creates new cracks. Over time, it even could result in the collapse of installed sewer pipelines. Longitudinal cracks that may appear on the sides, top, and the bottom of the pipes and also the deterioration of soil support around the pipes could deform the sewer pipelines or even make them entirely collapsed. This finding is in line with a study undertaken by (Davies, et al., 2001), in which it is mentioned that more than 10% deformation may result in the collapse of the pipelines (Zhao, et al., 2021; Salihu, et al., 2022).

Based on the above-mentioned observations, the complex interrelationships existing among the factors contributing to the failure of sewer pipelines can be developed using SDM. Emphasising the multi-dimensional and interdependent character of the deterioration process, Figure 6 offers a thorough representation of the complex web of elements and sub-factors causing sewer pipeline failure. The figure shows that rather than acting separately, structural, environmental, and operational components are closely related. External pressures like soil erosion, changing groundwater levels, and vehicle traffic loads exacerbate structural vulnerabilities such as ageing materials and joint misalignments, for example. At the same time, operational inefficiencies—such as postponed maintenance, inadequate inspections, and ongoing blockages—aggravate these structural and environmental pressures, therefore hastening the deterioration process. Especially, the number shows feedback loops whereby a decline in one area might intensify flaws in another; for instance, ground movement-related fractures might cause infiltration, which then aggravates corrosion and compromises the structural integrity of the pipe. This intricate interaction implies that efficient management of sewer infrastructure calls for a unified approach in which proactive maintenance, environmental monitoring, and structural reinforcement plans are coordinated globally. To properly forecast failures, give interventions top priority, and finally improve the durability and lifetime of sewer systems, one must first understand and handle these layered interactions.

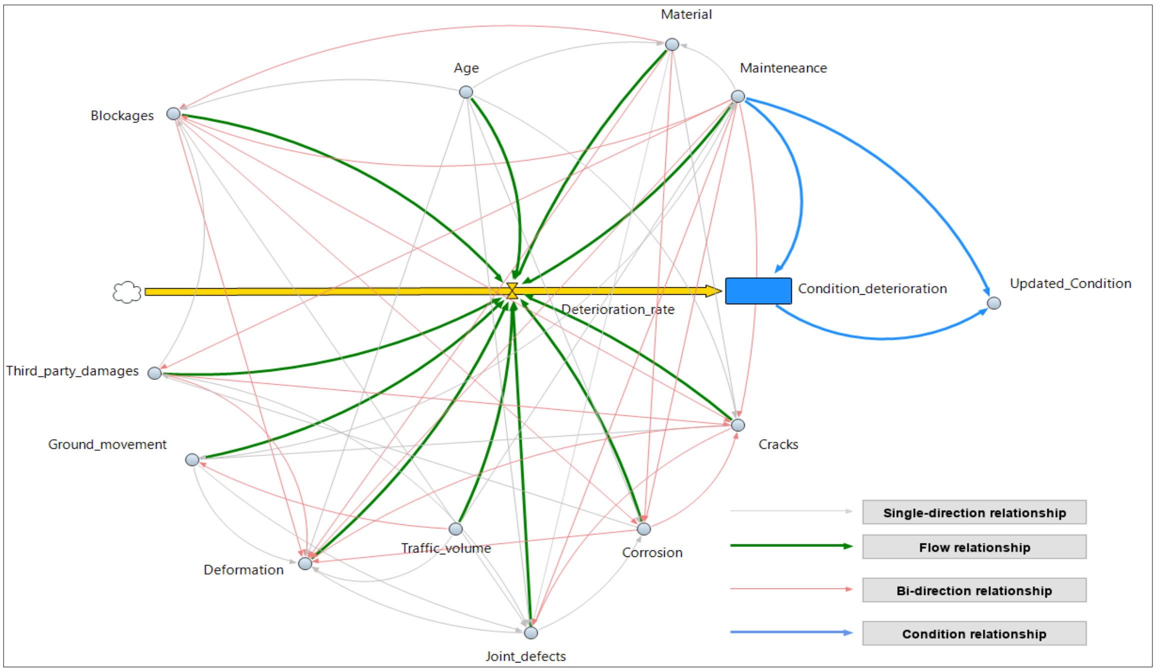


Figure 6: Complex Interrelationships among the factors and sub-factors contributing to sewer failure.

To validate the developed models and the identified critical factors contributing to sewer pipeline failure, as mentioned in the methodology section, a two-pronged approach was employed: triangulation using CCTV inspection data and expert interviews. A summary of sewer pipeline conditions in Hong Kong was created based on comprehensive CCTV inspection data provided by the DSD, utilizing the standardized Internal Condition Grade (ICG) system. This grading system, ranging from 1 (excellent) to 5 (complete failure), offered an objective and systematic representation of pipeline conditions across the network. Grades 4 and 5 were merged to represent the "failure condition," and approximately 10% to 15% of inspected pipelines exhibited major defects or failures, serving as a reliable proxy for real-world damage events. This quantitative validation ensured that the model outputs are grounded in field-based observations rather than theoretical constructs. Table 4 summarizes the distribution of pipeline conditions based on the available inspection records; approximately 10%–15% of the inspected pipelines were found to have severe defects or failure, which can be regarded as cases of critical damage (Abdelkhalek & Zayed, 2023).

Table 4: Distribution of pipeline conditions.

Condition Grade	Description	Approximate Proportion	Estimated Number of Records (Training + Testing)	Data Source
Grade 1 (G1)	Excellent condition	~40%	~12,000	CCTV Inspection Records (DSD)
Grade 2 (G2)	Minor defects	~30%	~9,000	CCTV Inspection Records (DSD)
Grade 3 (G3)	Moderate defects	~20%	~6,000	CCTV Inspection Records (DSD)
Grade 4–5 (G4)	Severe defects / Failures	~10%	~3,500	CCTV Inspection Records (DSD)

In parallel, validation through semi-structured expert interviews reinforced the significance of the identified critical factors. Participants admitted that operational practices (e.g., maintenance frequency, blockage occurrences), environmental factors (e.g., soil conditions, groundwater level, traffic loading), and structural characteristics (e.g., material, diameter, age) are intricately related and essential for knowledge of pipeline deterioration. Concerning the impact of pipe material, however, revealed a more subtle viewpoint. One specialist contended that although material qualities are very important, their function is mostly passive and reactive instead of dynamic. From this perspective, the ageing process and environmental exposure mostly hasten material degradation rather than actively affecting other deterioration mechanisms.

A cast iron pipe, for instance, might rust with time because of soil acidity or groundwater infiltration, but it does not directly cause joint displacements or soil movements. Thus, the material was regarded more as a receiver of outside stresses than a catalyst of system-wide degradation cascades. Moreover, certain authorities underlined that cumulative operational and environmental stresses could cause the efficacy of first material selection to fade over the service life, therefore blurring the line between the material's original resilience and its aged vulnerability. Some pointed out that while material by itself might not lead to systematic failures, certain materials—especially those prone to particular deterioration modes like corrosion in metal pipes and embrittlement in older PVC pipes—can exacerbate weaknesses when combined with outside influences, including high traffic or subpar bedding conditions. These revelations highlight the need to see sewer pipeline deterioration as a dynamic, multi-factorial process whereby material properties, environmental exposure, and operational history interact over time. They also confirm the need to include expert judgement with data-driven modelling to capture subtle, real-world complexity that might not be totally clear under quantitative analysis alone. While the subtle comments offer chances to improve the reading of interrelationships among contributing elements, the general consistency between expert views and the model framework greatly enhances the validity of the results.

4 Research Implications

This research offers a number of both theoretical and managerial implications as follows. As regards the theoretical implications, a detailed list of factors and the corresponding sub-factors driving the sewer pipelines to failure was put forward. Such exhaustive list lays down a solid foundation for the future researchers to use them in their studies. Furthermore, the prepared list can assist the researchers in developing their conceptual models in dealing with the maintenance of sewer pipelines. In addition to that, a novel hybrid method was proposed in this study, which is based on the integration of PFS with the traditional Delphi technique. The proposed technique will induce impetus among the researchers interested in the use of soft computing within the realm of infrastructure engineering and management towards the further improvements of combined fuzzy Delphi technique. On top of all that, researchers can use the proposed hybrid technique for capturing the maximum level of uncertainty associated with the problem to be dealt with in their studies.

Aside from the points mentioned above, this study provides several implications for the practitioners concerned with the drainage networks. Firstly, it provides the practitioners with a detailed list of factors and their related subs contributing to the failure of sewer pipelines. This is of paramount importance as mostly, if not always, in the common practices adopted by municipalities, the major focus has been given to a few factors for which quantitative data can be obtained (e.g., through CCTV-based analysis). In this way, many of the critical factors deteriorating the conditions of constructed sewer pipelines are not taken into account. More importantly, the garnered list of factors can open avenue for the concerned decision-makers to opt for leading-edge technologies, which provide them with more information on the conditions of sewers (in addition to the ones that can be obtained now with the existing technologies). Additionally, the prioritized list of factors and sub-factors provided in this study sheds light into the common practices, by drawing the attention of decision-makers concerned with the maintenance of sewer systems to the critical factors driving the pipelines to the complete failure at greater pace. Once the conditions of sewer pipelines have been improved, there will be less failure within the constructed systems. This leads to a significant decline in the magnitude of environmental-related hazards associated with such failure, such as overflow, exfiltration, to name but a few.

Building on the modelling results, it is important to consider how these findings can be translated into actionable strategies for infrastructure planning and decision-making. The findings of this study offer valuable, practical insights for infrastructure managers and decision-makers responsible for the maintenance of sewer networks. By systematically identifying and prioritising the most influential factors contributing to pipeline failure, the proposed PFDM framework provides a structured foundation for making well-informed maintenance decisions. In particular, assets situated in high-risk conditions such as aggressive soil environments or ageing materials can be proactively earmarked for inspection or rehabilitation. The integration of System Dynamics Modelling further strengthens this approach by offering a broader perspective on how deterioration factors interact and evolve over time. This enables decision-makers to anticipate potential failure scenarios and implement timely interventions, rather than relying on reactive responses. Ultimately, the insights derived from this model can assist in optimising resource allocation, guiding the development of risk-based maintenance strategies, and supporting strategic investment in monitoring technologies – contributing to a more resilient and cost-effective management of sewer infrastructure.

5 Limitations and Future Works

Even though this study offers a number of contributions to the body of relevant literature, it is imbued with some limitations to be tackled in future research:

1. This study uses purposeful sampling for the sake of data collection. Although the employment of such sampling leads to obtaining reflective results due to the strict criteria considered in this

research, it suffers from the aspect of generalizability. Thus, it is recommended using probability-based sampling in future research.
2. This study is limited by local specificity, material variations, and the dynamic urban infrastructure, potentially missing unforeseen factors; future research should explore regional influences, employ advanced predictive modelling, and consider climate change impacts, aiming to integrate real-time monitoring and develop targeted preventive measures to enhance infrastructure resilience.
3. Another limitation intertwined with this study is that the probability of the sub-factors to sewer failure has not been examined; thus, future research can be focused upon developing probability-based modelling for quantifying the likelihood of the occurrence of each factor towards the failure of pipes.
4. Although this study sought to anchor the model analysis in actual data, it should be emphasised that thorough public statistics on individual sewer pipeline damage cases—e.g., specific numbers of collapses or blockages—in Hong Kong are not easily accessible. The DSD mostly evaluates sewer pipeline condition using uniform CCTV inspections and assigns ICG depending on the observed structural state. This study used the Grade 4–5 category (severe defects/failure) as a proxy to reflect important pipeline damage events in the absence of direct damage case records. Though it limits direct quantification of absolute damage event counts, this method guarantees consistency with field observations. Future research could work directly with maintenance agencies to obtain thorough incident logs if they are available.

The outcomes of this study offer valuable insights to environmental and drainage decision-makers. By focusing their attention on the critical factors that contribute to sewer system failures, they can work towards reducing failure rates in all forms. This, in turn, will help in preserving various aspects of our environment affected by such failures, including sewer overflow, exfiltration, and many others.

Acknowledgements
The authors gratefully acknowledge the support from the Environment Conservation Fund (ECF) under grant number ECF/058/2019 and the Drainage Services Department (DSD) of the Government of Hong Kong for providing the required data and case study.

Funding
This research received no external funding.

Ethical Approval Declaration
The study was conducted in accordance with established standards for research integrity and ethics.

Informed Consent Statement
All participants provided informed consent before participating in the study.

Data Availability Statement
The data supporting the findings of this study will be made available by the authors upon reasonable request.

Conflicts of Interest
The authors declare no conflict of interest.

References

Alarifi, H., Mohandes, S. R., Salihu, C., Zayed, T., & Yan, J. (2021). A large-scale model of lateral pressure on a buried pipeline in medium dense sand. *Applied Sciences, 11*(12).

Ana, E., & Bauwens, W. (2010). Modeling the structural deterioration of urban drainage pipes: The state-of-the-art in statistical methods. *Urban Water Journal, 7*(1), 47–59.

Anbari, M., Tabesh, M., & Roozbahani, A. (2017). Risk assessment model to prioritize sewer pipes inspection in wastewater collection networks. *Journal of Environmental Management, 190*, 91–101.

Angkasuwansiri, T., & Sinha, S. K. (2013). Comprehensive list of parameters affecting wastewater pipe performance. *Technology Interface International Journal, 13*(2), 68–79.

Ariaratnam, S. T., El-Assaly, A., & Yang, Y. (2001). Assessment of infrastructure inspection needs using logistic models. *Journal of Infrastructure Systems, 7*(4), 160–165.

Baik, H.-S., Jeong, H. S., & Abraham, D. M. (2006). Estimating transition probabilities in Markov chain-based deterioration models for management of wastewater systems. *Journal of Water Resources Planning and Management, 132*(1), 15–24.

Bakry, I., Alzraiee, H., Kaddoura, K., & Zayed, T. (2016). Condition prediction for cured-in-place pipe rehabilitation of sewer mains. *Journal of Performance of Constructed Facilities, 30*(5).

Balekelayi, N., & Tesfamariam, S. (2019). Statistical inference of sewer pipe deterioration using Bayesian geoadditive regression model. *Journal of Infrastructure Systems, 25*(3).

Baur, R., & Herz, R. (2002). Selective inspection planning with ageing forecast for sewer types. *Water Science and Technology, 46*(6–7), 389–396.

Bouzon, M., Govindan, K., Rodriguez, C. M., & Campos, L. M. (2016). Identification and analysis of reverse logistics barriers using fuzzy Delphi method and AHP. *Resources, Conservation and Recycling, 108*, 182–197.

Caradot, N., Riechel, M., Fesneau, M., Hernández, N., Torres, A., Sonnenberg, H., Ber, E., Rouault, P., & Károlyi, A. (2018). Practical benchmarking of statistical and machine learning models for predicting the condition of sewer pipes in Berlin, Germany. *Journal of Hydroinformatics, 20*(5), 1131–1147.

Carvalho, G., Amado, C., Leitão, J. P., & Covas, D. (2018). Analysing the importance of variables for sewer failure prediction. *Urban Water Journal, 15*(4), 338–345.

Chan, A., Chan, D., & Yeung, J. (2009). Overview of the application of "fuzzy techniques" in construction management research. *Journal of Construction Engineering and Management, 135*(11), 1241–1252.

Cheng, J., & Wang, M. (2018). Automated detection of sewer pipe defects in closed-circuit television images using deep learning techniques. *Automation in Construction, 95*, 155–171.

Chughtai, F., & Zayed, T. (2007). Sewer pipeline operational condition prediction using multiple regression. *Advances and Experiences with Trenchless Pipeline Projects*, 1–11.

Chughtai, F., & Zayed, T. (2008). Infrastructure condition prediction models for sustainable sewer pipelines. *Journal of Performance of Constructed Facilities, 22*(5), 333–341.

Cortés, J., Pellicer, E., & Catala, J. (2012). Integration of occupational risk prevention courses in engineering degrees: Delphi study. *Journal of Professional Issues in Engineering Education & Practice, 138*(1), 31–36.

Cuong, B., & Kreinovich, V. (2013). Picture fuzzy sets—A new concept for computational intelligence problems. In *Third World Congress on Information and Communication Technologies (WICT 2013)*. IEEE.

Davies, J., Clarke, B., Whiter, J., & Cunningham, R. (2001). Factors influencing the structural deterioration and collapse of rigid sewer pipes. *Urban Water, 3*(1–2), 73–89.

Davies, J. P., Clarke, B. A., Whiter, J. T., & Cunningham, R. J. (2001). The structural condition of rigid sewer pipes: A statistical investigation. *Urban Water, 3*(4), 277–286.

Durdyev, S., Mohandes, S., Mahdiyar, A., & Ismail, S. (2022). What drives clients to purchase green building?: The cybernetic fuzzy analytic hierarchy process approach. *Engineering, Construction and Architectural Management, 29*(10), 4015–4039.

Egger, C., Scheidegger, A., Reichert, P., & Maurer, M. (2013). Sewer deterioration modeling with condition data lacking historical records. *Water Research, 47*(17), 6762–6779.

El-Housni, H., Ouellet, M., & Duchesne, S. (2018). Identification of most significant factors for modeling deterioration of sewer pipes. *Canadian Journal of Civil Engineering, 45*(3), 215–226.

Ennaouri, I., & Fuamba, M. (2013). New integrated condition-assessment model for combined storm-sewer systems. *Journal of Water Resources Planning and Management, 139*(1), 53–64.

Gupta, U. G., & Clarke, R. E. (1996). Theory and applications of the Delphi technique: A bibliography (1975–1994). *Technological Forecasting and Social Change, 53*(2), 185–211.

Han, L., Chen, Y., Chrysanthou, A., & O'Sullivan, J. (2002). Self-pierce riveting: A new way for joining structures. In *Proceedings* (pp. 123–127).

Hansen, B. D., Rasmussen, S. H., Moeslund, T. B., & Borup, M. (2021). Comprehensive feature analysis for sewer deterioration modeling. *Water, 13*(6).

Harvey, R. R., & McBean, E. A. (2014). Predicting the structural condition of individual sanitary sewer pipes with random forests. *Canadian Journal of Civil Engineering, 41*(4), 294–303.

Hawari, A., Alkadour, F., Elmasry, M., & Zayed, T. (2020). A state of the art review on condition assessment models developed for sewer pipelines. *Engineering Applications of Artificial Intelligence, 93*.

Henley, E., & Kumamoto, H. (1992). *Probabilistic risk assessment: Reliability engineering, design and analysis* (Vol. 1).

Hou, Y., Fang, Q., Zhang, D., & Wong, L. N. Y. (2015). Excavation failure due to pipeline damage during shallow tunnelling in soft ground. *Tunnelling and Underground Space Technology, 46*, 76–84.

Jiang, G., Keller, J., Bond, P. L., & Yuan, Z. (2016). Predicting concrete corrosion of sewers using artificial neural network. *Water Research, 92*, 52–60.

Kermanshachi, S., Rouhanizadeh, B., & Dao, B. (2020). Application of Delphi method in identifying, ranking, and weighting project complexity indicators for construction projects. *Journal of Legal Affairs and Dispute Resolution in Engineering and Construction, 12*(1).

Kerwin, S., & Adey, B. (2020). Optimal intervention planning: A bottom-up approach to renewing aging water infrastructure. *Journal of Water Resources Planning and Management, 146*(7).

Kleiner, Y., & Rajani, B. (2001). Comprehensive review of structural deterioration of water mains: Statistical models. *Urban Water, 3*(3), 131–150.

Krippendorff, K. (2013). *Content analysis: An introduction to its methodology*. Los Angeles, CA: Sage Publications.

Kuliczkowska, E. (2015). Analysis of defects with a proposal of the method of establishing structural failure probability categories for concrete sewers. *Archives of Civil and Mechanical Engineering, 15*(4), 1078–1084.

Kuliczkowska, E. (2016a). An analysis of road pavement collapses and traffic safety hazards resulting from leaky sewers. *The Baltic Journal of Road and Bridge Engineering, 11*(4), 251–258.

Kuliczkowska, E. (2016b). The interaction between road traffic safety and the condition of sewers laid under roads. *Transportation Research Part D: Transport and Environment, 48*, 203–213.

Kuliczkowska, E., & Bąba, K. (2018). An analysis of the categories regarding the probability of an operational failure of sewers. *Conference Proceedings*.

Kuzin, S., & Adams, B. (2005). Probabilistic approach to the estimation of urban stormwater pollution loads on receiving waters. In *Impacts of Global Climate Change* (pp. 1–12).

Le Gat, Y. (2008). Modelling the deterioration process of drainage pipelines. *Urban Water Journal, 5*(2), 97–106.

Li, D., Xiao, M., & Zeng, Q. (2003). Impact of deep excavations on adjacent buried pipelines. In *New Pipeline Technologies, Security, and Safety* (pp. 1116–1125). ASCE.

Li, H., Zhu, H., Zhang, C., Zhang, W., & Wu, J. (2019). Review of the state of the art: Interactions between a buried pipeline and frozen soil. *Cold Regions Science and Technology, 157*, 171–186.

Li, X., Khademi, F., Liu, Y., Akbari, M., Wang, C., Bond, P. L., Huang, J., & Jiang, G. (2019). Evaluation of data-driven models for predicting the service life of concrete sewer pipes subjected to corrosion. *Journal of Environmental Management, 234*, 431–439.

Liu, P., Li, Y., & Wang, P. (2022). Consistency threshold-and score function-based multi-attribute decision-making with Q-rung orthopair fuzzy preference relations. *Information Sciences, 618*, 356–378.

Liu, T., Ramirez-Marquez, J. E., Jagupilla, S. C., & Prigiobbe, V. (2021). Combining a statistical model with machine learning to predict groundwater flooding (or infiltration) into sewer networks. *Journal of Hydrology, 603*.

Lubini, A. T., & Fuamba, M. (2011). Modeling of the deterioration timeline of sewer systems. *Canadian Journal of Civil Engineering, 38*(12), 1381–1390.

Mahdiyar, A., Tabatabaee, S., Abdullah, A., & Marto, A. (2018). Identifying and assessing the critical criteria affecting decision-making for green roof type selection. *Sustainable Cities and Society, 39*, 772–783.

Malek Mohammadi, M., Najafi, M., Kermanshachi, S., Kaushal, V., & Serajiantehrani, R. (2020). Factors influencing the condition of sewer pipes: State-of-the-art review. *Journal of Pipeline Systems Engineering and Practice, 11*(4).

McDonald, S. E., Zhao, J. Q., & Kleiner, Y. (2001). *Guidelines for condition assessment and rehabilitation of large sewers*. Ottawa, ON: Institute for Research in Construction, National Research Council Canada.

Micevski, T., Kuczera, G., & Coombes, P. (2002). Markov model for storm water pipe deterioration. *Journal of Infrastructure Systems, 8*(2), 49–56.

Mohammadi, M., Najafi, M., Kaushal, V., Serajiantehrani, R., & Salehabadi, N. (2019). Condition prediction of sanitary sewer pipes. In *Pipelines 2019* (pp. 117–126). Reston, VA: American Society of Civil Engineers.

Mohandes, S., Sadeghi, H., Mahdiyar, A., Durdyev, S., Banaitis, A., Yahya, K., & Ismail, S. (2022). Evaluation of the critical factors causing sewer overflows through modeling of structural equations and system dynamics. *Journal of Cleaner Production, 375*.

Mohandes, S., Sadeghi, H., Mahdiyar, A., Durdyev, S., & Ismail, S. (2022). Causal analysis of accidents on construction sites: A hybrid fuzzy Delphi and DEMATEL approach. *Safety Science, 151*.

Mohandes, S., & Zhang, X. (2019). Towards the development of a comprehensive hybrid fuzzy-based occupational risk assessment model for construction workers. *Safety Science, 115*, 294–309.

Mohmoodian, M. (2013). *Reliability analysis and service life prediction of pipelines* (Doctoral dissertation). University of Greenwich.

Najafi, M., & Gokhale, S. B. (2005). *Trenchless technology: Pipeline and utility design, construction, and renewal* (1st ed.). New York, NY: McGraw-Hill Education.

Najafi, M., & Kulandaivel, G. (2005). Pipeline condition prediction using neural network models. In *Pipelines: Optimizing Pipeline Design, Operations, and Maintenance in Today's Economy* (pp. 767–781).

Nile, B., & Shaban, A. (2019). Investigating lateral soil-sewer pipe displacements under indirect horizontal loads. *ARPN Journal of Engineering and Applied Sciences, 14*, 1–15.

Okoli, C., & Pawlowski, S. (2004). The Delphi method as a research tool: An example, design considerations and applications. *Information & Management, 42*(1), 15–29.

Okwori, E., Viklander, M., & Hedström, A. (2021). Spatial heterogeneity assessment of factors affecting sewer pipe blockages and predictions. *Water Research, 194*.

Rifaai, T., Abokifa, A., & Sela, L. (2022). Integrated approach for pipe failure prediction and condition scoring in water infrastructure systems. *Reliability Engineering & System Safety, 220*.

Rutsch, M., Rieckermann, J., Cullmann, J., Ellis, J. B., Vollertsen, J., & Krebs, P. (2008). Towards a better understanding of sewer exfiltration. *Water Research, 42*(10–11), 2385–2394.

Saegrov, S. (2005). *Computer aided rehabilitation of sewer and storm water networks*. London, UK: IWA Publishing.

Salihu, C., Hussein, M., Mohandes, S., & Zayed, T. (2022). Towards a comprehensive review of the deterioration factors and modeling for sewer pipelines: A hybrid of bibliometric, scientometric, and meta-analysis approach. *Journal of Cleaner Production, 351*.

Salman, B., & Salem, O. (2012). Modeling failure of wastewater collection lines using various section-level regression models. *Journal of Infrastructure Systems, 18*(2), 146–154.

Scheidegger, A., Hug, T., Rieckermann, J., & Maurer, M. (2011). Network condition simulator for benchmarking sewer deterioration models. *Water Research, 45*(16), 4983–4994.

Simic, V., Karagoz, S., Deveci, M., & Aydin, N. (2021). Picture fuzzy extension of the CODAS method for multi-criteria vehicle shredding facility location. *Expert Systems with Applications, 175*.

Sousa, V., Matos, J. P., & Matias, N. (2014). Evaluation of artificial intelligence tool performance and uncertainty for predicting sewer structural condition. *Automation in Construction, 44*, 84–91.

Syachrani, S., Jeong, H., & Chung, C. (2011). Dynamic deterioration models for sewer pipe network. *Journal of Pipeline Systems Engineering and Practice, 2*(4), 123–131.

Syachrani, S., Jeong, H., & Chung, C. (2013). Decision tree–based deterioration model for buried wastewater pipelines. *Journal of Performance of Constructed Facilities, 27*(5), 633–645.

Tabatabaee, S., Mahdiyar, A., Mohandes, S., Ismail, S., & Momeni, M. (2022). Investigating the barriers to applying the Internet-of-Things-based technologies to construction site safety management. *International Journal of Environmental Research and Public Health, 19*(2).

Tan, Y., & Lu, Y. (2018). Responses of shallowly buried pipelines to adjacent deep excavations in Shanghai soft ground. *Journal of Pipeline Systems Engineering and Practice, 9*(2).

Tanoli, W. A., Sharafat, A., Park, J., & Seo, J. W. (2019). Damage prevention for underground utilities using machine guidance. *Automation in Construction, 107*.

Tee, K., Khan, L., Chen, H., & Alani, A. (2014). Reliability based life cycle cost optimization for underground pipeline networks. *Tunnelling and Underground Space Technology, 43*, 32–40.

Tran, H. (2007). *Investigation of deterioration models for stormwater pipe systems* (Doctoral dissertation). Victoria University.

Wirahadikusumah, R., Abraham, D., & Iseley, T. (2001). Challenging issues in modeling deterioration of combined sewers. *Journal of Infrastructure Systems, 7*(2), 77–84.

Xu, M., Shen, D., & Rakitin, B. (2017). The longitudinal response of buried large-diameter reinforced concrete pipeline with gasketed bell-and-spigot joints subjected to traffic loading. *Tunnelling and Underground Space Technology, 64*, 117–132.

Yin, X., Chen, Y., Bouferguene, A., & Al-Hussein, M. (2020). Data-driven bi-level sewer pipe deterioration model: Design and analysis. *Automation in Construction, 116*.

Younis, R., & Knight, M. (2010). A probability model for investigating the trend of structural deterioration of wastewater pipelines. *Tunnelling and Underground Space Technology, 25*(6), 670–680.

Zhao, Y., Ma, B., Ariaratnam, S. T., Zeng, C., Yan, X., Wang, F., Wang, T., Zhu, Z., & He, C. (2021). Structural performance of damaged rigid pipe rehabilitated by centrifugal spray on mortar liner. *Tunnelling and Underground Space Technology, 116*.