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Review

A Comprehensive Review of the Key Deterioration Factors of Concrete Bridge Decks

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Abstract: Bridges are generally acknowledged as one of the vital structures of transportation systems. Meanwhile, they are prone to time-variant damage and deterioration mechanisms over their life span. With that in mind, this research study aims to explore state-of-the-art work in relation to deterioration models and related critical factors of reinforced concrete bridges. Particularly, this study presents a mixed review methodology (scientometric and systematic) that reviews over 300 publications in Scopus and Web of Science databases over the period 1985–2023. The study scrutinized and categorized the wide spectrum of deterioration factors in reinforced concrete bridges with the help of deterioration models. Results manifested that implicating deterioration factors can be grouped into seven main clusters, namely chemical, material properties, design & construction, physical, operational, environmental, and force majeure. In addition, it is noted that hitherto, there has been a lack of sufficient research efforts on non-destructive evaluation-based deterioration models.

Keywords: concrete bridges; deterioration factors; deterioration prediction; non-destructive evaluation; scientometric analysis; systematic review

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1. Introduction

Bridges play a crucial role in connecting highways and cities, facilitating movement between different geographical areas [1,2]. However, due to aging and frequent usage, the deterioration of these structures intensifies over time. According to the American Society of Civil Engineers (ASCE), in 2017, 9.1% of the bridges in the country were classified as structurally deficient. Likewise, the American Association of State Highway and Transportation Officials (AASHTO) in 2007 declared that about 40% of the bridges had reached the age of 50 years and were nearing the end of their expected lifespan of 75 years [3]. The deterioration of structures presents a notable obstacle for transportation organizations responsible for maintaining civil infrastructure, such as bridges. The maintenance, repair, and replacement (MR&R) of collapsed bridges need massive financial investments, which impose a huge obligation on transportation organizations. To optimize resource allocation for new construction and rehabilitation projects, departments of Transportation (DOTs) have increasingly collected data on bridge conditions and conducted thorough analyses. As a result, greater efforts and funds are now dedicated to the maintenance and rehabilitation of existing bridges. Consequently, developing effective bridge management systems becomes imperative to enhance data organization and utilization, enabling the efficient planning and suitable execution of maintenance processes [4].

Extending the service life of current bridges is crucial for preserving existing mobility and minimizing the expenses associated with bridge maintenance and repairs. To effectively optimize bridge maintenance requirements, it is imperative to gain a comprehensive understanding of the parameters that influence the performance of various types of concrete bridges. Consequently, bridge authorities allocate a substantial portion of their annual budgets towards the maintenance and repair of bridges [3]. Moreover, improving the service life of current bridges will aid in preserving their functionality and decreasing the expenses associated with their maintenance and repairs. To effectively optimize bridge maintenance requirements, it is crucial to comprehend the factors that influence the performance of concrete bridges. Concrete bridge decks deteriorate over time due to various causes, such as construction defects, poor maintenance, chemical corrosion, climatic conditions, extreme flooding, erosion, etc. [5]. Figure 1 displays the deterioration of a bridge deck caused by rainwater seeping through the initial cracks and through the damaged waterproof layer, followed by chloride intrusion due to the stagnation of saltwater and further leakage of water through the deck. It is essential to identify and control the reasons that lead to bridge deterioration to effectively maintain bridges, in addition to repairing the damage. Identifying these factors helps in analyzing cause and effect, diagnosing the damage, and modeling bridge deterioration. This improves the accuracy of predictions and reduces the overall expenses during the lifespan of the bridge. Due to the crucial importance of these factors in ensuring operational functionality and safety, regular inspections and renewals are carried out to evaluate the state of bridge components. As a result, many academics have concentrated on creating deterioration models that consider the influence of operating circumstances, environmental factors, mechanical properties, and physical characteristics. Moreover, Figure 2 illustrates some bridge deterioration cases, possibly due to weather and loading conditions.

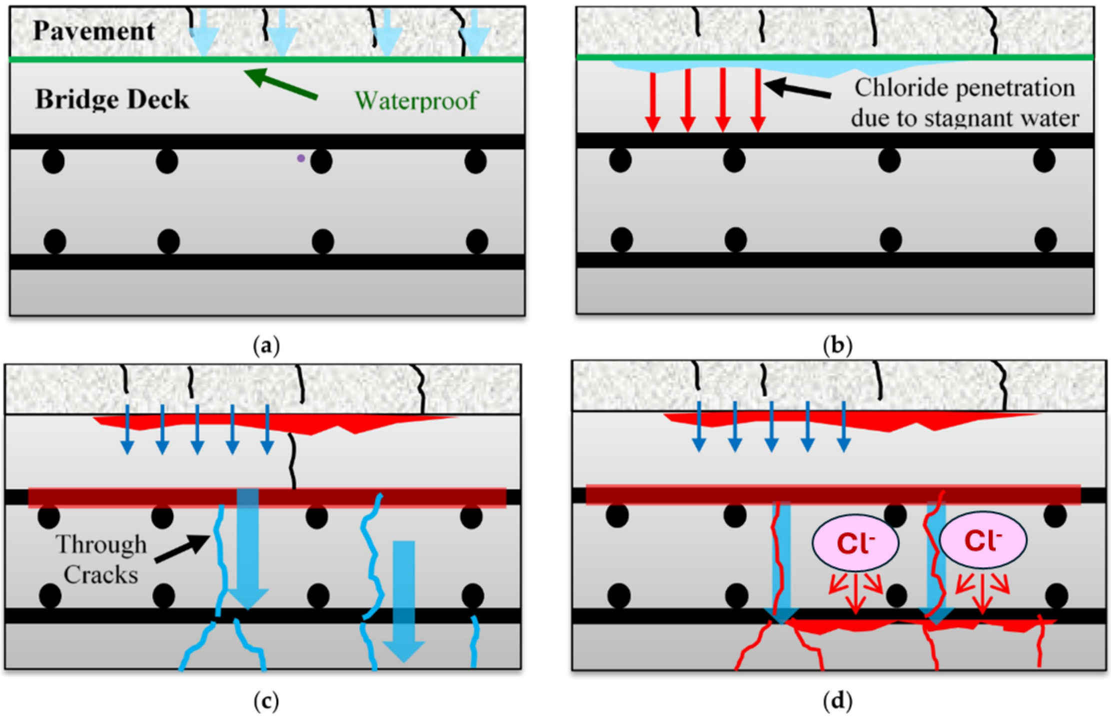

Figure 1. Bridge deck composition and deterioration mechanism: (**a**) Rainwater penetration due to initial cracks and damage to the waterproof layer; (**b**) Chloride penetration into the deck top surface due to the stagnant water with salt; (**c**) Water leakage to the deck bottom surface due to crack propagation; (**d**) Corrosion of steel reinforcement at the bottom and damage to the deck bottom surface. (Reproduced from Ref. [6] Copyright (2020) MDPI).

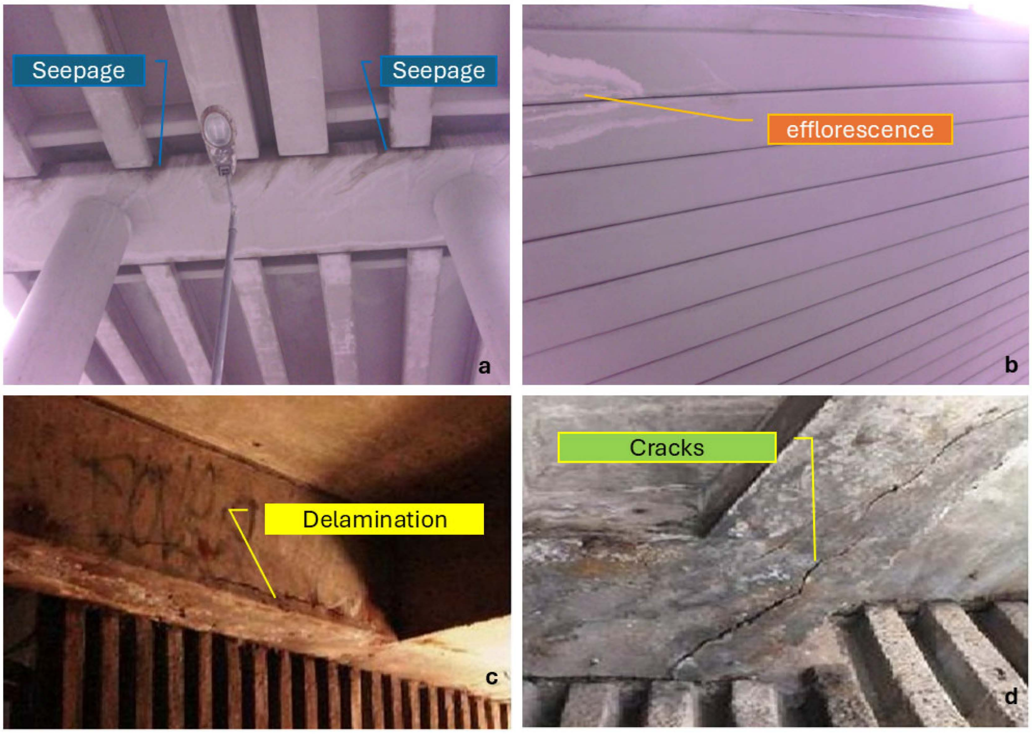

Figure 2. Bridge deterioration cases: (**a**) Seepage; (**b**) Efflorescence; (**c**) Delamination; (**d**) Cracks. (Reproduced from Ref. [7] Copyright (2016) Elsevier).

Bridge maintenance is a crucial component of the bridge's lifespan, involving a range of actions that can have substantial effects on the environment. These operations encompass short-term measures, such as capital preventative maintenance (CPM), that are designed to mitigate deterioration, enhance functioning, and extend the operational lifespan of the bridge. Medium-term solutions involve rehabilitation, encompassing structural improvements to enhance the roadway or bridge deck overlay. Long-term solutions involve the reconstruction or replacement of bridge components [8,9]. Bridge maintenance must prioritize sustainability, emphasizing the use of eco-friendly materials, energy-efficient building processes, and environmentally sensitive maintenance procedures. Incorporating sustainable practices not only reduces environmental impact but also contributes to long-term cost savings and enhances the overall resilience of bridges [10,11].

After conducting an extensive review of the existing literature, a significant research deficiency has been revealed concerning the factors that contribute to the deterioration of concrete bridge decks. It is important to mention that there is a lack of comprehensive review studies that thoroughly investigate these elements despite their significant role in the field. This highlights the necessity of conducting a thorough literature study that examines the elements contributing to the deterioration of concrete bridge decks and systematically assesses the effectiveness of existing deterioration models. The identified research gap has served as the driving force behind the authors' motivation to present readers with a comprehensive review of deterioration models and factors influencing the degradation of concrete bridge decks. To contribute to the existing body of knowledge, this study employs a hybrid review methodology that integrates both scientometric and systematic review approaches. By adopting this holistic review framework, this study offers a comprehensive understanding of the deterioration modeling of concrete bridge decks. By integrating scientometric analysis, which provides insights into the trends and patterns in the published literature, with systematic review techniques, which facilitate a rigorous and structured examination of the available research, this study encompasses a broad and in-depth analysis of the topic. Through this hybrid review approach, the study aims to uncover the key critical factors that contribute to concrete bridge deck deterioration by evaluating the existing deterioration models for concrete bridge decks.

This study addresses a critical gap in the existing literature concerning the factors that contribute to the deterioration of concrete bridge structures, especially decks. Despite the significant impact these factors have on bridge safety and longevity, there are needs for more comprehensive reviews that thoroughly investigate and analyze them. This gap underscores the necessity for a detailed literature study that explores the elements contributing to deterioration and systematically assesses the effectiveness of existing deterioration models. The identified research deficiency is the driving force behind this study, motivating the authors to present a comprehensive review of deterioration models and the factors influencing the degradation of concrete bridge decks. By employing a hybrid review methodology that integrates both scientometric and systematic review approaches, this study aims to make a significant contribution to the existing body of knowledge. This holistic review framework offers a nuanced understanding of concrete bridge deck deterioration, integrating insights from scientometric analysis to identify trends and patterns in the published literature and systematic review techniques that facilitate rigorous and structured examinations of the available research. Through this hybrid approach, the study seeks to uncover critical factors contributing to concrete bridge deck deterioration and evaluate the efficacy of existing deterioration models. By highlighting these elements, this research enhances our understanding of bridge maintenance challenges and provides valuable insights for practitioners and policymakers in improving bridge infrastructure sustainability and safety.

The remainder of the review paper is structured as follows. Section 2 outlines the research methodology adopted for this review, detailing the approach used to gather and analyze the relevant literature. Sections 3 and 4 present the findings obtained from the scientometric and systematic reviews, offering comprehensive insights into research trends and the assessed importance of deterioration models and factors. Finally, the latter sections summarize the main findings and highlight implications for future research, bridge deck management, and conclusions.

2. Research Methodology

This study followed a mixed review methodology approach. The mixed review method encompasses quantitative (scientometric approach) and qualitative (systematic approach) review methodologies. The use of the mixed review approach is widely acknowledged by numerous researchers owing to its capacity to mitigate biased conclusions and subjective interpretations while simultaneously facilitating a comprehensive comprehension of domain expertise and research patterns [12–14]. This study employed a unique approach to identify and extract deterioration factors from the literature. The scientometric analysis was conducted on data related to bridge deterioration models, which helped identify relevant studies. On the other hand, the systematic review focused on extracting deterioration factors from the literature. The use of scientometric analysis allowed for a targeted and data-driven approach to identify relevant studies in the field of bridge deterioration models. This ensured that the selected studies were directly related to the research topic and provided valuable insights into the factors considered by researchers in their deterioration models. By leveraging this approach, the study aimed to capture realistic factors and parameters that were consistently adopted and considered in bridge deterioration models rather than relying on random factors obtained from the literature. This study determined the deterioration models and related factors contributing to the deterioration of concrete bridge decks as part of this investigation. Overall, the review seeks to identify the critical factors that contribute to concrete bridge deck deterioration; a categorization of these factors based on their nature will be carried out, allowing for a structured understanding of their impact on the deterioration process.

Bridge deterioration modeling marks an integral pillar of maintenance management systems, and its accuracy inevitably signifies the efficaciousness of bridge management [15,16]. Hitherto, artificial intelligence (AI)-driven models established themselves as a powerful mechanism to anticipate future performance conditions of bridge elements. In this respect, the accuracies of these models are triggered by the proper identification of input deterioration [17,18]. With that in mind, it is paramount to determine and prioritize the factors that implicate the deterioration behavior of bridge elements.

This study aims to thoroughly examine, classify, map, and evaluate research publications related to models and deteriorating factors of concrete bridge decks. The study provides a thorough overview of the subject during this timeframe, ranging from 1985 to the end of 2023. Figure 3 explicates the proposed framework schema for this study.

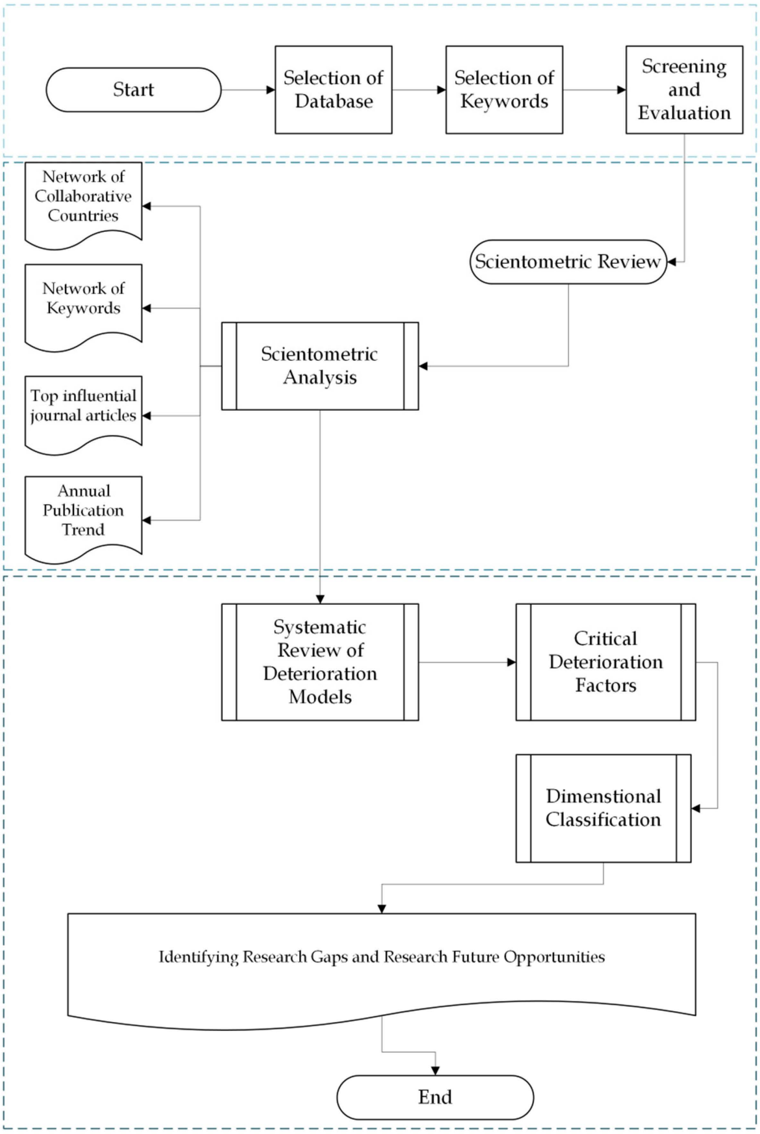

Figure 3. Research framework.

2.1. Data Collection

2.1.1. Exploring Scientific Databases: An In-Depth Search Process

According to Baker and Algorta [19], including multiple databases in a systematic review is essential to obtaining a comprehensive collection of pertinent articles. Therefore, documents for this study were retrieved from two literature databases, Web of Science and Scopus.

2.1.2. Keyword Selection and Boolean Query Strings

To execute the literature search, two Boolean query strings were constructed for Web of Science (WoS), and Scopus. The 'title/abstract/keyword' element of the Scopus and WoS search engines was utilized to search for multiple sets of keywords with the Boolean concatenator 'OR & AND' to ensure comprehensive coverage. The complete search strings for WoS and Scopus were designed covering "Bridge*" AND (Concrete OR prestressed) AND ("deterioration factors" OR "deterioration model" OR "deterioration predict*" OR "deterioration forecast*").

The aim was to explore the broad spectrum of deterioration factors as well as specific factors in deterioration models to obtain the maximum and most realistic factors from the collected data.

2.1.3. Evaluation of Retrieved Studies

Consequently, 149 and 205 manuscripts were identified from the Web of Science and Scopus databases, respectively, as depicted in Figure 4.

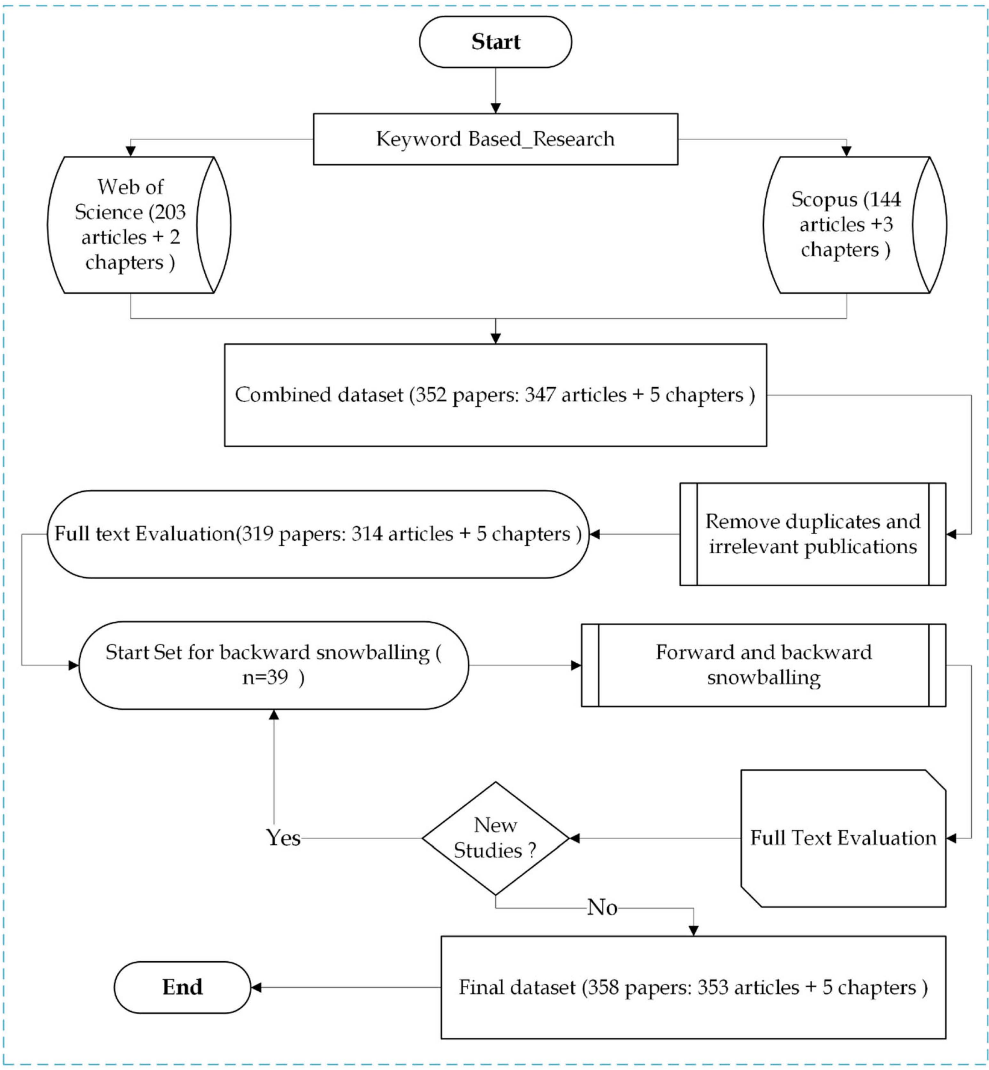

Figure 4. Scientometric Analysis (Screening and Evaluation).

Following this, a screening process eliminates duplicate and out-of-scope studies from the merged database. In this regard, 33 studies were deemed irrelevant after their abstracts, entire texts, and titles had been reviewed. Consequently, 352 documents were produced, consisting of 349 articles and three book chapters.

2.1.4. Snowballing

The authors performed a snowballing search on the initial set of articles, supplementing forward and backward snowball search methods to identify any missing publications relevant to the scope of this research study, as suggested by Wohlin [20]. This is resolved through a search of pertinent articles utilizing the reference lists and citing articles from individual papers [21,22]. Citations linked to individual papers were captured by Google Scholar in this context. The forward and reverse search strategies yielded a total of 12 papers. After including these papers, the final dataset expanded to a total of 331 papers, comprising 328 articles and three book chapters.

2.2. Scientometric Review and Systematic Review

Scientometric review is a mapping technique utilized in quantitative science. The primary objective is to represent the dynamic and structural elements of scientific inquiry. Scientometric review utilizes text-mining techniques [23]; therefore, this approach eliminates the element of subjectivity that is commonly found in narrative and systematic reviews [24]. Subjectivity ensues when the researcher employs their interpretation to extract data from the retrieved studies, subsequently utilizing said data for analysis. Bibliometric and scientometric analyses are conducted using the VOSviewer tool [25].

Although the results derived from the scientometric review approach are valuable for delineating the research domain, they do not offer a comprehensive understanding of the bibliometric data. In contrast, the objective of a systematic review is to provide a comprehensive overview of current research to detect deficiencies in the knowledge base and predict possible directions for future research [26]. The methodology of systematic literature review (SLR) is a highly effective approach that has been employed within the field of construction engineering and management (CEM) to clarify the scope of current research and highlight potential topics for future study exploration [27]. Without systematic reviews, the field tends to foster a community heavily focused on strict empiricism, hindering the theoretical progress of the area. By conducting systematic reviews, researchers can break free from this entrenched convention and promote a more comprehensive and robust theoretical foundation in CEM research.

In the data collection phase, the studies were collected focusing on the deterioration models for concrete bridges via designed keywords, and overall, 331 documents (328 journal articles and three book chapters) were collected. These collected studies were analyzed via performing scientometric analysis for concrete bridges' deterioration models, and details on the different types of adopted models were studied. Later, in the second phase, using data from deterioration models, the critical deterioration factors for concrete bridges were extracted by systematically reviewing the details against models and their significant parameters or factors. However, to analyze the factors contributing to the deterioration of concrete bridge decks, a binary response statistic was incorporated into the review process. The binary response statistic was employed to gather and ascertain all the predictors utilized in the extant literature. Consequently, supplementary measures were used to extract these predictors for the modeling procedure. Subsequently, the predictors were categorized and employed to execute the binary response statistic. The conclusive outcomes yielded significant numerical findings that hold worth for both researchers and professionals.

3. Scientometric Analyses

On the collected 331 documents, the following analyses were performed, i.e., (1) temporal distribution of related research studies, (2) keyword co-occurrence analysis, (3) countries' co-authorship analysis, and (4) document analysis.

Figure 5 visualizes countries' collaboration in deterioration factors and models of bridges (DET_FMB) research, such that a minimum number of documents and citations were set to 1 and zero, respectively. As a result, a total of 46 countries met the specified thresholds, and four colored clusters were identified accordingly. It is evident that the United States of America maintained the highest collaboration level around the globe, with a total link strength of 41. In this respect, the United States of America had its greatest collaboration with Canada (link strength = 8) and China (link strength = 5). In addition, Canada and China attained the second (21) and third (16) most total link strength all over the world. Table 1 elucidates the countries contributing most to the DET_FMB domain. It is revealed that the literature was led by the United States of America (143 documents, 3997 citations), Canada (41 documents, 1212 citations), and China (48 documents, 599 citations). According to average normalized citations, India (1.81), Japan (1.54), and the United Arab Emirates (1.50) come in the first three places.

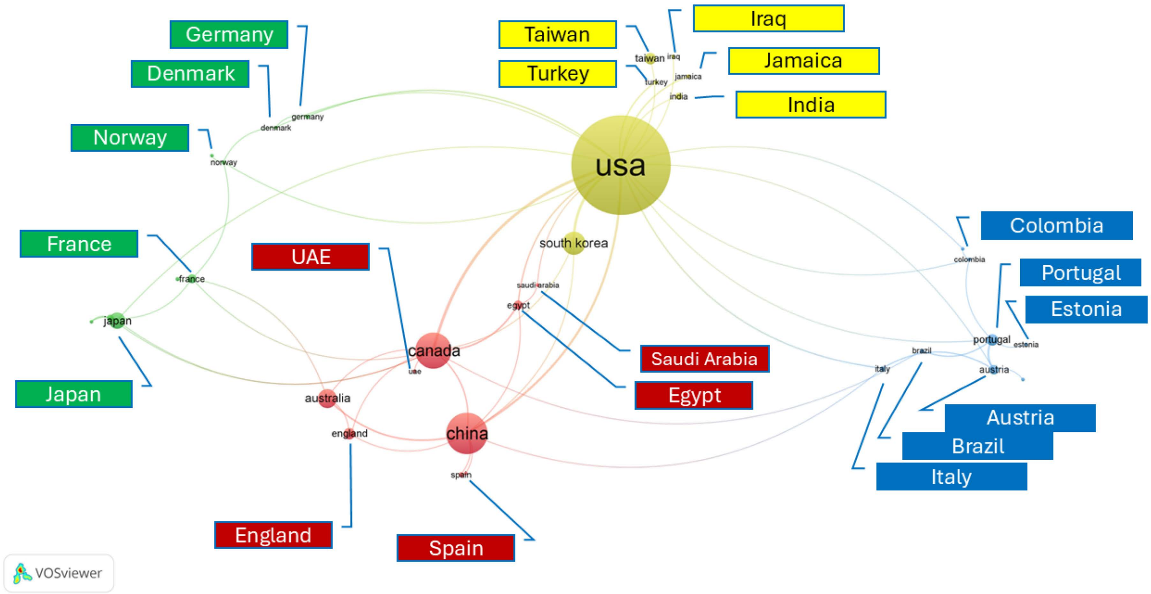

Figure 5. Co-authorship network of countries in the domain of DET_FMB.

Table 1. Top active countries in the research on DET_FMB.

Rank	Country	Number of Documents	Total Citations	Total Link Strength
		Publication count		
1	United States of America	143	3997	41
2	China	48	599	16
3	Canada	41	1212	21
4	Republic of Korea	23	302	9
5	Australia	18	259	6
		Total citations		
1	United States of America	143	3997	41
2	Canada	41	1212	21
3	China	48	599	16
4	Republic of Korea	23	302	9
5	Japan	15	296	5

Keyword co-occurrence analysis elucidates the current state of DET_FMB research. Figure 6 shows the keyword co-occurrence network, where keywords appearing at least twice were selected, resulting in 80 keywords. The analysis identified three clusters with a resolution of 1 and a minimum cluster size of 12. The red cluster (37 nodes) focuses on deterministic and stochastic deterioration models and key deterioration factors, featuring keywords like “bridge deterioration” and “deep learning”. The blue cluster (18 nodes) pertains to reliability analysis and maintenance management, with keywords such as "maintenance optimization" and "Bayesian updating". The green cluster emphasizes mechanistic deterioration models and service life prediction, including keywords like "corrosion" and "service life prediction".

The keyword co-occurrence analysis reveals the predominant focus on visual inspection-based deterioration models rather than non-destructive ones. Ground penetrating radar, half-cell potential, electrical resistivity, and impact echo emerge as dominant non-destructive techniques for deterioration forecasting. Markovian decision processes and artificial neural networks are the widely used methods for condition prediction. Probability distribution-based models predominantly employ Weibull and gamma distributions for predictive analysis. Machine learning models are more commonly used than deep learning models, while feature selection-based artificial intelligence still needs to be explored. Mechanistic models primarily explore chloride and corrosion propagation. Maintenance optimization models rely on Markov chain and reliability analysis rather than artificial intelligence. Table 2 summarizes frequent keywords and their co-occurrence count and link strength. Prominent author keywords include 'deterioration model', 'reinforced concrete bridge', 'bridge management system', 'corrosion', 'maintenance optimization', 'Markov chain', and 'condition assessment'.

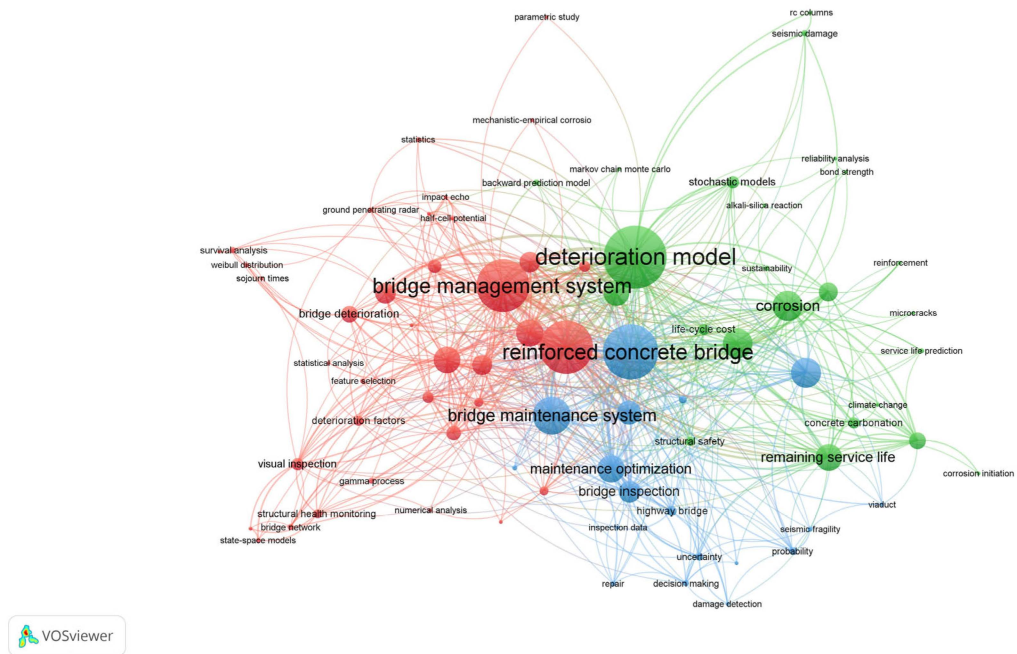

Figure 6. Keyword co-occurrence network of author keywords in DET_FMB research.

Table 3 synthesizes the top articles from the perspectives of total citations. The most cited article is entitled "Estimation of Infrastructure Transition Probabilities from Condition Rating Data". In this article, order probit models were constructed to characterize infrastructure deterioration in each condition state, such that they estimated coefficients of relevant explanatory variables like age, average daily traffic, climatic conditions, wearing surface type, structural type, and classification of the roadway.

Figure 7 displays the yearly publication trend of DET_FMB research from 1984 until November 2023. Initial publications from 1984 to 1996 lie in the exploration period, whereas the production rate did not exceed two papers per annum. After that, the publication went through a consolidation period (1997–2012), whereas there was a mild pace in the publication growth. The publication production then flourished and rose dramatically after that until 2023, with an annual average of 21 papers and a maximum of 35 papers in 2020. It is worth mentioning that the flourishing period accounts for an emphatic 70.39% of total publication output. A fourth-order polynomial function was constructed for the annual publication growth as follows: $APR = 6.3065E-6YR^4 - 0.0497YR^3 + 146.5967YR^2 - 1.9227E+5YR + 9.457E+7; R^2 = 89.40\%$, such that APR is the annual publication rate and YR stands for the publication year under consideration.

Table 2. Quantitative summary of main co-occurring keywords in DET_FMB research.

Keyword	Occurrences	Total Link Strength
Deterioration model	67	173
Reinforced concrete bridge	57	163
Reinforced concrete deterioration	55	170
Bridge management system	54	142
Bridge maintenance system	36	111
Time-dependent reliability	27	53
Corrosion	27	83
Reinforced concrete	26	82
Maintenance optimization	24	78
Markov chain	24	77
Condition assessment	23	75

Table 3. Top influential journal articles in the DET_FMB domain based on number of citations and normalized citations.

Rank	Reference	Journal	Total Citations	Key Findings
1	[28]	Journal of Infrastructure Systems	241	Ordered probit model outperformed typical Markovian models in estimation of condition ratings
2	[29]	Journal of Infrastructure Systems	190	Stochastic duration models could efficiently calibrate transition probability matrices
3	[30]	Journal of Structural Engineering	154	Coefficient of variation of deterioration imitation time sustain slight influences on cumulative time-failure probability of bridge girder systems
4	[31]	Journal of Infrastructure Systems	152	A random effects-based probit model could accommodate heterogeneity of bridge condition dataset
5	[32]	Automation in Construction	133	A genetic algorithm-based model was proposed for maintenance optimization of concrete bridge decks

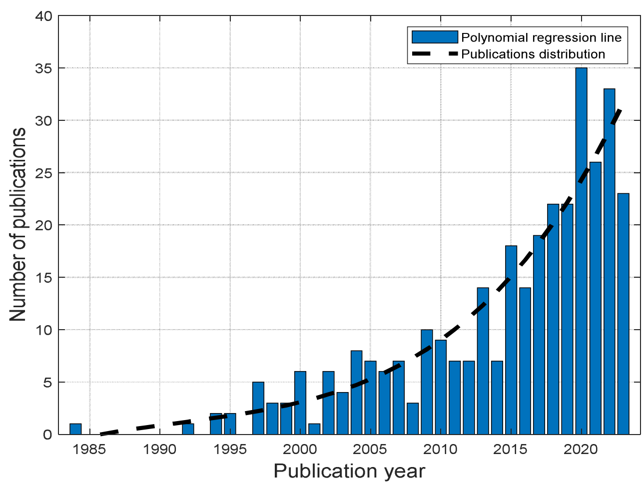

Figure 7. Annual production of DET_FMB-related research.

4. Discussion

4.1. Bridges Deterioration Models

This literature review (based on 331 studies) reveals various bridge deterioration models developed by the researchers; however, generally, the collected data supports three bridge deterioration model categorizations, i.e., deterministic, stochastic, and mechanistic. Each model category has some advantages and limitations compared to the others. With the help of AI models, researchers are trying to compensate for such shortcomings, and such models are known as AI models. Thus, the bridge deterioration models can broadly be distributed under four categories. The deterioration models used in the literature are elucidated in Figure 8.

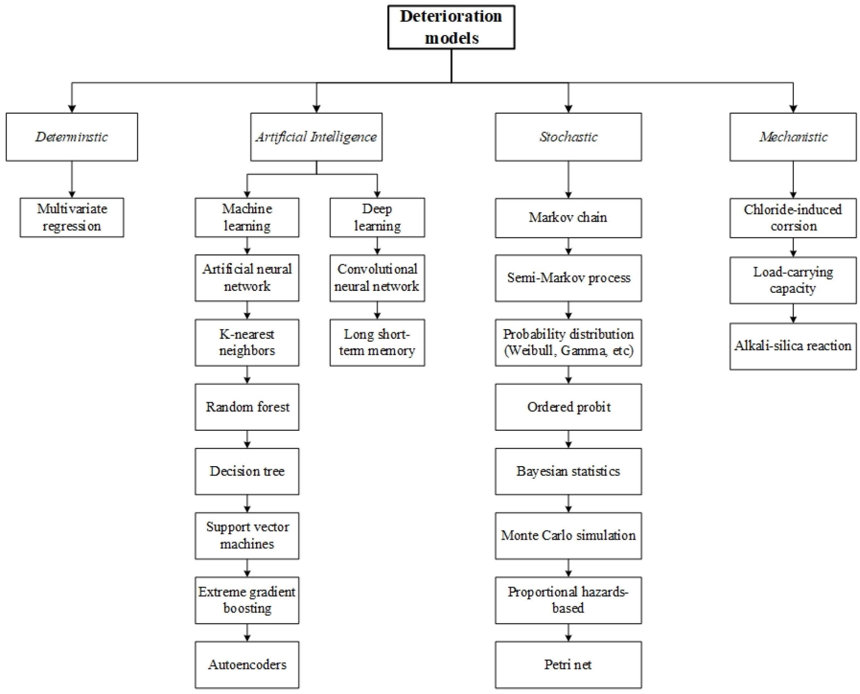

Figure 8. Types of bridge deterioration models.

4.1.1. Deterministic Models

The deterministic models define bridge elements' conditions using specific values under a certain time, i.e., the tendency of the bridge deterioration is assumed to be certain by following regression analysis (using historical data for estimating deterioration rate); however, the models can be straight-line extrapolation, regression, and curve-fitting models. The empirical relationship among model variables affects the outcome, i.e., one or more independent variables and one dependent variable. Compared to non-linear regression models, linear regression models are considered less accurate for prolonged performance assessments of bridges as, under a specific time, they may overestimate and underestimate the bridge condition. These models are considered accurate for short-term condition predictions. These models consider conditions at the project execution stage and after the project completion stage; they lack the rate of deterioration prediction for repair stages. The literature reveals that for the bridge condition assessment, the accuracy of mathematical models such as curve fitting is dependent on polynomials, giving the best fit for bridge data. In this regard, the condition rating of bridge element versus age was found to be a better predictive model, especially for concrete bridges [33]. Moreover, bridge material conditions can be predicted by using straight-line extrapolation models, albeit by assuming that maintenance history and traffic loading follow a straight line. A common form of deterioration can be assessed as Equation (1).

$$\frac{C_d}{t_d} = -k \times C^n \tag{1}$$

where 'C_d' is the condition stage of the bridge, 't_d' is deterioration time, 'k' is deterioration constant, and 'n' reflects the sensitivity of deterioration to the condition state. The deterministic models follow a simple future prediction approach for bridge conditions; therefore, they are understandable and show practicality at the network level. However, deterministic models are not able to link or interact with the deterioration of various bridge elements (such as deck joints, bridge deck, etc.). Moreover, new data computation in the model is expensive. Furthermore, the deterministic model ignores uncertainty due to the inherent stochastic nature of infrastructure deterioration.

4.1.2. Stochastic Models

Due to the complex and erratic behavior of deteriorated elements, the nature of the stochastic model is considered closer to the deterioration process than the deterministic model. Moreover, stochastic models can manage the deterioration process-based uncertainties in better ways and are generally categorized into Markov chain models, simulation, and probability distribution. Likewise, for bridges, the stochastic models may consider multiple variables such as the bridge's element condition, time, etc., and may project the uncertain nature of the deterioration process. In general, stochastic models predict the future trend based on the past behavior of the element. In reference to this, the Markov process is considered a conditional stochastic process as future trends are predicted based on the present behavior of the element, ignoring the past trend. This theory facilitates the computations by keeping the data simple; however, these considerations are not supported by a mechanistic knowledge of material behaviors [34]. The advantage of the Markov model is the consideration of identified discrete condition inspection states, which describe each possible change in condition in the simplest possible way at equal intervals. However, one of the limitations is linked to the derivation of transition probabilities, whereas, in the case of complete, significant, and consistent data, the transition probabilities could be estimated via adopting regression-based optimization methods, the ordered probit model, the expected-value method, and the percentage prediction method. In contrast, expert judgment elicitation or simulation techniques may be adopted. The stochastic process follows geometric Brownian motion to assess the deterioration rate, as shown in Equation (2).

$$C_d(t) = \mu \times C \times (t) \times t_d + v \times C(t) \times W_d(t) \tag{2}$$

where 'μ' reflects the drift coefficient, 'v' is volatility, and '$Wd(t)$' is the wiener process. The probability distribution reflects the associated probable values of all random variables, which requires information on the variable and distribution process for the prediction. Another way to deal with a large number of uncertain scenarios is via simulation for attaining precise values, such as Monte Carlo simulation, which has been widely adopted for concrete-based bridge deterioration models as it could consider both the input variable and sensitivity probability distribution for analyzing the scenario. The simulation helps to draw/predict probabilistic deterioration profiles over time to change from one condition rating to another.

The majority of Markovian models advocate the use of the Markovian decision process in their work. However, the most challenging task is the calibration of transition probability matrices. Several methods were proposed in the literature to address this issue, such as the Bayesian network and Metropolis–Hastings [35], genetic algorithm [36], cluster analysis with the percentage prediction method [37], and generalized Poisson-Binomial distribution [38]. In another study reported by Collins and Weidner [39], they investigated five different methods of calibrating transition probability matrices, which were Bayesian maximum likelihood (BML), nonlinear optimization (NLO), ordered probit modeling (OPM), proportional hazards-based modeling (PHM), and Poisson and negative binomial-based modeling (PNBM). Thereafter, a combined transition probability matrix was generated by averaging the transition probability matrices of the aforementioned methods. Hasan and Elwakil [40] designed a Monte Carlo simulation-based model for projecting bridge deck conditions. In this model, a best-fit distribution was assigned for each of the input continuous variables like deck, width, structural length, and percentage of average daily truck traffic.

Researchers have classified stochastic models as: (1) time-based models and (2) state-based models. The time-based model states that "the duration that a bridge element remains at a particular condition state is modeled as a random variable using probability distributions", such as Gamma distribution, Weibull distribution, etc. However, in state-based models, on the other hand, the modeling is performed considering the transition (from one condition state to another) probability in a discrete time interval. Markov chains are the most adopted technique under state-based models, assuming the deterioration process depends on various measurable variables such as material, climate, annual average daily traffic, and age.

4.1.3. Mechanistic Models

The efficacy of Markovian models heavily relies on the computation of transition probability matrices [41]. Unreliable transition probability matrices result in errors in the condition evaluation of bridge elements, and this subsequently leads to inaccurate maintenance budgets [42,43]. With that said, mechanistic models are adopted to overcome the Markov chain model's limitation in reference to relating condition state's qualitative measurements of the bridge physical quantitative parameters (such as structural behavior, stress conditions, failure modes, material properties, etc.); such parameters are considered as critical assessment data for the reliability and structural capacity of bridges [44,45]. The mechanistic models are capable of explaining the particular deterioration phenomena linked with specific bridge elements, describing the deterioration as a quantitative performance indicator through knowledge of the chemical and physical processes occurring at that instant [43]. For example, the corrosion rate can be assessed using Faraday's Law, as shown in Equation (3). In contrast, the power law can be used to assess material degradation, as shown in Equation (4).

$$\frac{M_d}{t_d} = \frac{I}{m \times F} \tag{3}$$

$$\frac{d_\sigma}{d_t} = -k \times \sigma^n \tag{4}$$

where 'M_d' is the mass of the corrosion product, 'I' is the corrosion product, 'm' is the number of electrons transferred, 'F' is the constant value, 'σ' is stress, and 'n' reflects the sensitivity exponent.

In another attempt, Mizutani et al. [46] estimated Markovian transition probabilities by modeling chloride-induced corrosion during the initial and propagation phases. In their work, Fick's second law of diffusion was used to simulate chloride penetration (see Equation (5)), and cracks were assumed to take place after some chloride concentration. The work of Lethanh et al. [47] is another research endeavor that addressed the transition probabilities of decks subjected to chloride-induced corrosion. In this research, the corrosion propagation of reinforcement was modeled according to their cross-section loss. In addition, the crack propagation mechanism was evaluated using Equation (6), by considering chloride-induced corrosion, cracks, and ambient environmental conditions in developing their Markovian deterioration models. The impact of relative humidity on the diffusion process ($f_{RH}(t)$) was accounted for using Equations (7) and (8). Furthermore, the corrosion rate (mm/year) subject to temperature variations was evaluated using Equation (9).

$$\frac{\partial C_{cl}}{t} = D_{cl}\frac{\partial^2 C_{cl}}{\partial x^2} \tag{5}$$

$$w(t) = w_0 + \beta\,(P(t) - P_0) \tag{6}$$

$$f_{RH}(t) = exp\left(1 - \frac{(100 - RH_{Av}(t))^4}{(100 - 75)^4}\right)^{-1} \tag{7}$$

$$RH_{Av}(t) = \frac{\sum_{i=t_1+1}^{t} RH(t)}{t - t_1} \tag{8}$$

$$i_{corr}(t) = i_{corr,20}[1 + K(T(t) - 20)] \tag{9}$$

where C_{cl} is the concentration of chloride ions at the depth of reinforcement, D_{cl} and x represent the chloride diffusion coefficient and depth, respectively, $w(t)$ is the width of the crack over time, w_0 is the width of the visible crack, β is a propagation constant, $P(t)$ is the loss in rebar diameter at the time t, P_0 is the loss in rebar diameter when visible cracks are present, $i_{corr,20}$ is the corrosion rate at a temperature of 20 °C, and K is a parameter that reflects the dependency of conductivity on temperature T.

The following instances are some implementations of mechanistic models by researchers: (1) to predict bridge deterioration via using load-carrying capacity, (2) to assess bridge concrete deformation considering effects of shrinkage, creep, and alkali–silica reaction, and (3) the calculation of corrosion initiation time by considering significant parameters, including exposure conditions, chloride binding capacity, relative humidity, and ambient temperature [48]. The mechanistic modeling technique gives reliability-based quantitative deterioration prediction for bridge elements, and it is appropriate for project-level analysis. However, a mechanistic-based deterioration model is not suitable for large bridge networks as its modeling and data requirements are costly. Moreover, due to high on-site data collection costs, these models cannot be directly integrated into building management systems.

4.1.4. Artificial-Intelligence (AI) Based Models

AI models have been developed for particle swarm optimization, shuffled frog leaping, genetic algorithms, case-based reasoning, artificial neural network (ANN), and the expectation maximization approach [49]. Researchers such as Mašović and Hajdin [50] followed the Markov chain model, modeled the deterioration of concrete bridge elements, and integrated the expectation maximization approach for calculating the transition probabilities on gathered data; a reasonable deterioration model was achieved irrespective of limited inspection records. Moreover, researchers have also generated artificial historical bridge condition states by adopting ANN models [51]. ANN general model operation is described as Equation (10). Meanwhile, model training generally follows the mean squared error theme, as explained in Equation (11).

$$Y = f\left(W^{(L)} \times f\left(W^{(L-1)} \ldots f\left(W^{(L)}x + b^{(1)}\right) + b^{(L-1)}\right) + b^{(1)}\right) \tag{10}$$

$$L(y, \tilde{y}) = \frac{1}{n}\sum_{i=1}^{n}\ (y_i - \tilde{y}_i)^2 \tag{11}$$

where '$W^{(L)}$' is the weight matrix for layer L, '$b^{(L)}$' is the bias vector for layer L, 'f' is the activation function, 'y_i' reflects the actual condition index, and '$\tilde{y}_i$' is the predicted condition index. Another study, by Bu et al. [52], integrated state-based and time-based model approaches by considering bridge elements and were able to achieve long-term prediction models. The time-based model used the Kaplan and Meier approach to estimate the probability distribution function of transition times, and the state-based model utilized Elman Neural Networks and the Markov chain for the calculation of transition probabilities.

The AI-based models, especially ANN models, are capable of generating missing condition state data, which helps fill the gaps that may be due to poor inspection. However, ANN models are good for generating missing data points, but for data analysis, other integrated tools or approaches are required. In contrast, an AI approach, such as case-based reasoning, can also be tested for analyzing various maintenance scenarios considering different maintenance decisions and retrieving cases with similar decisions based on available maintenance data [53]. However, the performance of the case-based reasoning model is dependent on the case library size, case description adequacy, correct attribute weights, and accessibility of knowledge for case adaptation. In the field of bridge engineering, machine learning-based deterioration predictive models have been developed to support the best preliminary structural design of bridges [54,55].

Artificial intelligence-based models are of a data-demanding nature and aim to study the condition index based on correlating it with a set of explanatory independent variables like age, area, number of lanes, skewness, traffic volume, and weather conditions, among others [56]. In this regard, some research attempts principally counted on some machine learning modes in predicting future conditions. This encompasses the use of artificial neural networks, genetic algorithm-based artificial neural networks, artificial neural networks with case-based reasoning [57] and autoencoder random forest [58]. Omar and Moselhi [59] compared the performances of random forest (RF), K-nearest neighbors (KNN), ANN, and deep neural network (DNN) in forecasting bridge deck conditions. They pointed out that random forest was the most efficient prediction model, accomplishing training and testing accuracies of 93.87% and 93.82%. In another study, Martinez et al. [4] carried out a comparison between predictive analysis models of artificial neural networks, decision trees (DT), deep learning neural networks (DLNN), K-nearest neighbors, and linear regression (LR). They evinced that the decision tree was the best-performing model according to cross-validation and statistical significance analysis. In a third study, Assaad and El-Adaway [60] evaluated the predictive capabilities of artificial neural networks and K-nearest neighbors. The manual tuning of their hyperparameters was undertaken to boost their performance. It was derived that the optimized ANN was able to outperform the optimized KNN, yielding a testing accuracy of 91.44%. Another group of artificial intelligence-based models capitalized on deep learning in bridge deterioration mimicking, such as convolutional neural networks and long short-term memory networks [61].

4.2. Bridge Deterioration Factors

In this phase, the relevant articles were sorted under the four deterioration model types (as discussed in the above section); overall, 110 out of 331 articles were found relevant, and significant data on the critical deterioration factors were extracted from the selected studies.

The deterioration process refers to the gradual decline or degradation of something over time. Deterioration factors play a critical role in modeling the deterioration of bridge decks, as they are the primary inputs for accurate predictions. Therefore, it is crucial to thoroughly analyze and assess these characteristics as "predictors" to determine their suitability for the employed modeling methods. The assessment is commonly conducted through binary response analysis, which facilitates the identification of pertinent predictors and their influence on the deterioration process. A binary response analysis is utilized in research scenarios when variables exhibit two distinct outcomes: success or failure. This research methodology is consistent with the principles of the binomial distribution, which is used to model a single Bernoulli trial. In the present distribution, success is conventionally denoted by the numerical value '1', and failure is defined by the numerical value '0' [62]. This study is employed to find the components of the deterioration models and categorize them into suitable classifications. Following this, a frequency analysis is performed to organize the elements according to their frequency of recurrence in the studies on deterioration modeling, i.e., "frequency was calculated based on the number of studies that considered this factor". Applying these foundational procedures to the chosen 110 articles, the variables are methodically monitored, retrieved, and arranged within a Microsoft Excel spreadsheet. Each element was assigned a binary value of '1' if employed in the study article and '0' if not. The data were subsequently analyzed to determine the frequency of each factor. By considering the total number of articles (110), the frequency percentage was calculated. Upon an analysis of the obtained results, it is evident that the elements found can be categorized into seven unique classifications: chemical, material properties, design & construction, physical, operational, environmental, and force majeure. Table 4 provides a detailed overview of the statistical data related to binary responses. Analyzing binary responses and assessing the identified seven categories comprehensively offers valuable insights for future research initiatives.

Table 4. Deterioration factors.

S No	Category	Factors	Frequency	%	Category Order
1.	Material properties	Materials type	19	17.28	1
2.		Tensile strength of steel	5	4.55	6
3.		Compressive strength of concrete	7	6.37	5
4.		Water-cement ratio	9	8.19	4
5.		Type of wearing surface	16	14.55	2
6.		Steel coating or passive protection	10	9.10	3
7.		Thermal mismatch between cements and aggregates	2	1.82	8
8.		Porosity	3	2.73	7
9.	Chemical	De-icing with salts/chloride	52	47.28	1
10.		Alkali—silica reaction	6	5.46	3
11.		Alkali—carbonate reaction	4	3.64	5
12.		Acid attack	5	4.55	4
13.		Concentration of carbon dioxide	18	16.37	2
14.	Design & Construction	Bridge length	25	22.73	1
15.		Bridge width	21	19.10	2
16.		Concrete cover	17	15.46	4
17.		Steel bar diameter	5	4.55	9
18.		Structure type	21	19.10	2
19.		Elevation	3	2.73	11
20.		Number of lanes	7	6.37	7
21.		Maximum span	16	14.55	5
22.		Type of girder	2	1.82	12
23.		Skewness	11	10.00	6
24.		Support Type	1	0.91	13
25.		Thickness of Deck	18	16.37	3
26.		Cross-beam spacing	1	0.91	13
27.		Direction of traffic	4	3.64	10
28.		Poor quality of concrete	6	5.46	8
29.	Physical	Distance from the coast	7	6.37	3
30.		Bridge age (years in service)	36	32.73	1
31.		Highway classification	11	10.00	2
32.		Type of service on bridge	5	4.55	5
33.		Type of service under bridge	6	5.46	4
34.	Operational	Average daily traffic	48	43.64	1
35.		Average Daily Truck Traffic	18	16.37	2
36.		Future Average Daily Traffic	1	0.91	6
37.		Inspection (frequency, precision, etc.)	4	3.64	5
38.		Maintenance actions for superstructure, substructure, & deck	14	12.73	3
39.		Drainage leakage	6	5.46	4

Table 4. *Cont.*

S No	Category	Factors	Frequency	%	Category Order
40.	Environmental	Temperature	23	20.91	1
41.		Scour critical bridges	5	4.55	6
42.		Vegetation growth	1	0.91	10
43.		Humidity	17	15.46	3
44.		Freeze & thaw cycles	21	19.10	2
45.		Precipitation	17	15.46	3
46.		Pollution	2	1.82	9
47.		Moisture content/variation	11	10.00	4
48.		Wind activity	2	1.82	9
49.		Dry weather	3	2.73	8
50.		Settlement	4	3.64	7
51.		Snowfall	7	6.37	5
52.	Force Majeure	Fire	1	0.91	3
53.		War/bomb damage	2	1.82	2
54.		Natural disasters (earthquake, typhoon, flood, etc.)	7	6.37	1

4.2.1. Material Properties

The "Material properties" category encompasses factors that account for the variations in the materials utilized in bridge construction. In this category, there are eight factors outlined in Table 4. The first factor, "Material type", considers the influence of material variations, e.g., cement type, aggregate type, and admixtures, employed in constructing the structure elements. Undoubtedly, this factor significantly impacts the performance of any structure along its service life. This was proven for different infrastructures, such as sewer and stormwater pipes [63] and water mains [64]. Expanding on the previous factor, the "type of wearing surface" factor pertains to the protective layer applied to the surface of concrete elements, i.e., most probably for bridge decks. Since the bridge deck is the element that provides the service to the bridge users, it is subjected to various deterioration factors, such as traffic impact, de-icing salt, accidents, etc. As a result, it deteriorates faster than other bridge components. Accordingly, most of the bridge authorities commonly apply an overlay layer to the bridge deck to extend its service life. The most used type is asphalt overlay; however, other overlay layers are used. Lin et al. [65] mentioned seven types of overlay layers that can be used, including epoxy, latex-modified concrete, silica fume-modified concrete, polyester polymer, asphalt with a liquid membrane, asphalt with a sheet membrane, and asphalt without a membrane.

The composition of concrete is another crucial aspect influencing the deterioration process of concrete elements. Previous studies mainly focused on the "water-cement ratio" factor. Water is added to concrete for two primary purposes: cement reactions and workability. A higher water–cement ratio results in the presence of free water in concrete, which is not involved in cement reactions. This free water can either find its way to the concrete surface or become trapped within the concrete. In the first scenario, the water carries some cement particles to the surface, while in the second scenario, this water evaporates over time, forming voids. Both scenarios lead to a reduction in concrete strength.

When investigating the deterioration factors for concrete structures, it is crucial to consider two significant characteristics of the materials used: "tensile strength of steel" and "compressive strength of concrete" [66]. These two characteristics/factors describe the bridge's ability to withstand the subjected loads. Over time, defects, such as cracks and corrosion, influence these two characteristics, i.e., reduce their values. Subsequently, they impact the bridge's overall performance in terms of load-bearing capacity and remaining service life.

Corrosion is considered one of the common deterioration mechanisms in reinforced concrete [67]. Reinforcing rebars are naturally protected by the high alkalinity of surrounding concrete and an adequate concrete cover [68]. However, two common factors initiate the corrosion process: chloride, most probably from de-icing salts, and carbonation. Rebars' corrosion can directly reduce the structural capacity of the reinforced concrete elements, which can cause internal stress, cracking, and delamination [69]. In order to protect reinforcing rebars from corrosion, steel protection methods, represented by the "steel coating or passive protection" factor, are employed as proactive measures. Several methods can be utilized, including cathodic protection, coating, and concrete surface coating [70].

The "Porosity" factor quantifies the volume of voids within concrete, establishing a relation between this factor and concrete strength. Additionally, the presence of these voids has a significant impact on freeze and thaw phenomena. If these voids are interconnected, i.e., cracks can create connections between voids, the permeability of concrete increases, facilitating the penetration of liquids and expediting its deterioration. The last factor, "thermal mismatch between cement and aggregates", indicates the degree of incompatibility in thermal properties between the cement and aggregate. This aspect is important, particularly in places or during some seasons where concrete is exposed to high temperatures. In such cases, a thermal mismatch between concrete components may lead to various deterioration mechanisms, such as cracking, which can escalate rapidly in the event of fire exposure.

The "Materials type" factor was the most frequently cited factor among other factors in this category. It was cited 19 times in the database, which represents 17.28%. Following this factor, "type of wearing surface", "steel coating or passive protection", and "water-cement ratio" factors came in the second, third, and fourth places, respectively. They were cited 16 (14.55%), 10 (9.10%), and 9 (8.19%) times in the filtered papers, respectively. The remaining factors were less cited. In total, they were cited 17 times, seven times for "compressive strength of concrete", five times for "tensile strength of steel", three times for "porosity", and twice for "thermal mismatch between cements and aggregates". The average citation score for the factors in this group was 8.875 times per factor. Figure 9 illustrates a spider chart for factors in the materials category along with their frequency number.

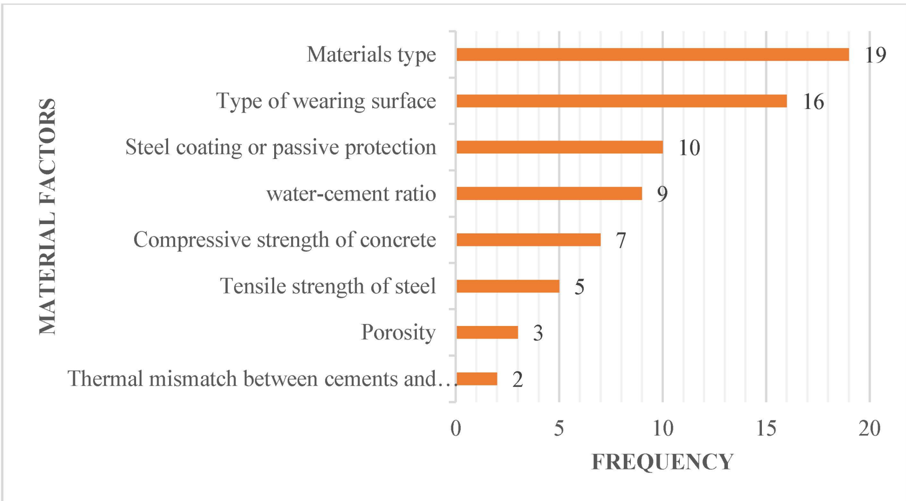

Figure 9. Bar chart for the material category.

4.2.2. Chemical Properties

Chemical factors play a significant role in the degradation of concrete bridge decks. "De-icing salts, such as chloride" are chemical compounds frequently employed to dissolve ice and snow on roadways and bridges in winter weather conditions. Chloride-based de-icers, such as calcium chloride or sodium chloride (rock salt), are used on bridge decks to decrease water's freezing point and prevent ice development. However, the existence of de-icing salts, specifically chloride ions, might cause harmful consequences on bridge decks as time advances. Upon contact with the bridge deck surface, de-icing salts can infiltrate the concrete or asphalt layers. The phenomenon of chloride ingress can cause corrosion [71]. "Alkali-silica reaction (ASR)" and "alkali-carbonate reaction (ACR)" are additional chemical processes that result in concrete cracking and weakening due to reactions between some cement compositions [72]. ASR is a chemical process between the alkalis (sodium and potassium) in concrete and specific kinds of silica minerals commonly found in aggregates used for making concrete. The reaction creates an alkali–silica gel, a gel-like substance that expands and applies force on the surrounding concrete structure. Over a period, the exerted force might result in the formation of cracks and the enlargement and decay of the concrete, weakening its structural strength [73]. ACR is a chemical reaction between alkalis in concrete and certain types of carbonate rocks present in aggregates, such as limestone or dolomite. The reaction forms a gel-like substance, like the alkali–silica gel in ASR. This gel formation can cause the concrete's expansion, cracking, and overall deterioration, like the effects of ASR [74]. "Acid attack", called acid corrosion or acid degradation, is the concrete deterioration in bridge decks due to exposure to acidic substances. Acidic substances, such as sulfuric acid, hydrochloric acid, or organic acids, can cause acid attacks when they come into contact with concrete. Acids react with the calcium hydroxide (lime) and other alkaline constituents in the cement matrix when encountering concrete. This chemical reaction results in the dissolution of calcium-based compounds, such as calcium hydroxide and calcium silicate hydrates, which play a crucial role in the durability and strength of concrete [75]. Moreover, "concentration of carbon dioxide (CO_2)" can lead to carbonation, reducing the concrete's alkalinity and compromising its protective layer [76].

The primary root cause of the degradation of reinforced concrete structures is the corrosion of reinforcing bars caused by chloride contamination. The corrosion arises when chloride ions infiltrate the concrete, undermining the protective passive oxide layer on the steel reinforcement and separating the outer layer of concrete [77]. Design codes impose restrictions on the permissible chloride content in concrete. However, chloride ions can still be introduced by external sources. Chloride ingress encompasses many transportation mechanisms, such as penetration, absorption, capillary suction, and diffusion [78]. The infiltration of chloride ions also enables the penetration of water and oxygen, which initiates corrosion on the surface of the steel. This process of corrosion results in the creation of rust and intensifies the degradation process. Leakage in deck expansion joints can result in saltwater infiltration, leading to the corrosion of the girder ends and steel bearings. The degradation of reinforcing materials is predominantly caused by corrosion resulting from chloride infiltration and carbonation [79]. The infiltration of chloride happens at a higher rate compared to carbonation and might lead to early decay, hence diminishing the lifespan of the building [80]. This has prompted many researchers to study this impact; for example, He et al.'s [81] study presents an innovative integrated diffusion-limited aggregation (DLA) model that effectively simulates the deterioration process of reinforced concrete bridges. This model focuses explicitly on the effects of chloride attack, carbonization, and their combined impact on the durability of these structures. These are some of the common environmental factors that influence the durability of FRP-concrete bonds. Alkaline environments can cause the corrosion of steel reinforcement or the deterioration of some types of FRP [82].

As shown in Figure 10, various factors influence the degradation of reinforced concrete bridges, as highlighted in a literature review. The most frequently mentioned factor, discussed 52 times, representing 47.28%, is de-icing with salts/chloride. This accelerates the corrosion of reinforcing steel in concrete, compromising structural integrity and durability. The concentration of carbon dioxide mentioned 18 times, representing 16.37%, can cause concrete carbonation, reducing its alkalinity and weakening its structure. Acid attacks, mentioned five times, can chemically break down the concrete, affecting its strength and durability. The alkali–silica reaction, mentioned six times, can severely impact concrete, causing the formation of an expansive gel, cracking, and deterioration. The alkali–carbonate reaction, mentioned four times, can also degrade concrete by forming harmful compounds.

The factors in this category were cited 85 times in 110 papers, representing 77.30%. Understanding these factors and their frequency in the literature provides a comprehensive understanding of reinforced concrete bridge degradation, enabling effective maintenance and management strategies for these crucial infrastructure assets.

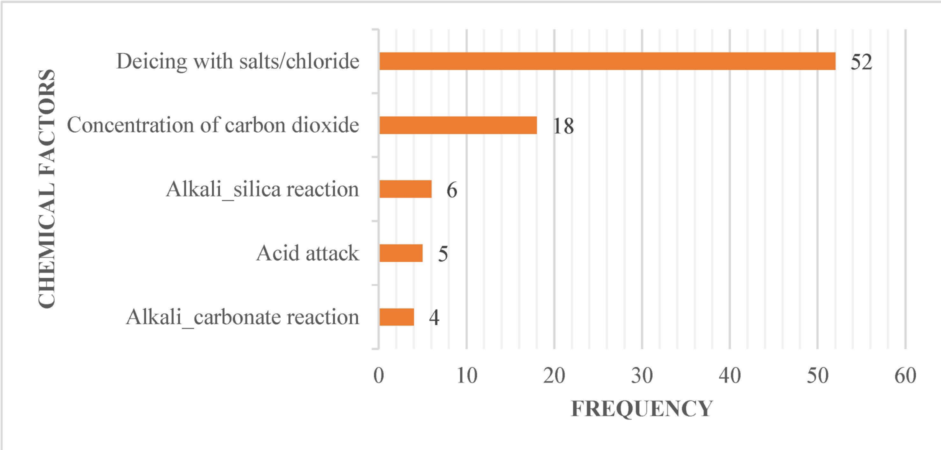

Figure 10. Bar chart for chemical properties.

4.2.3. Design and Construction

The deterioration of concrete bridge decks can be attributed to various design and construction factors. These factors include the bridge length and width, concrete cover, steel bar diameter, structure type, elevation, number of lanes, maximum span, type of girder, skewness, support type, the thickness of the deck, cross-beam spacing, the direction of traffic, and the poor quality of concrete.

The load-bearing capacity and stress distribution on a bridge deck is affected by its dimensions, including length, width, and the specific structure it supports [83]. The life span and strength of the deck are greatly influenced by factors such as the thickness of the concrete cover, the diameter of the steel bars, and the reinforcement [84]. Furthermore, the load and traffic conditions the deck undergoes are affected by various factors such as construction type, elevation, number of lanes, maximum span, and kind of girder [61]. Skewness, support type, deck thickness, and cross-beam spacing can generate uneven stress distribution and could degrade the deck [40]. Moreover, the orientation of traffic movement and the caliber of concrete employed in the building can also influence the degradation mechanisms. Comprehending these design and construction variables is crucial for adopting efficient maintenance and preservation techniques to guarantee concrete bridge decks' durability and structural soundness.

The width of a bridge is of the highest priority in both design and traffic management, as researchers are specifically studying the effects of width modifications on performance and stability. Likewise, the magnitude of a bridge poses difficulties that necessitate meticulous examination of support systems and materials. The study examines the correlation between bridge length, design factors, cost consequences, and feasibility to encourage effective and sustainable approaches [85].

Some researchers investigate the correlation between variables, such as bridge age, length, width, skew degree, and deck width, and their impact on bridge deterioration, as shown in Figure 11. Miao et al. [17] employed bridge length and breadth as input variables for neural network models to forecast degradation levels and examine their statistical significance. In addition, they explore the influence of altitude and find a negative relationship with the degree of deterioration. Similarly, Xia et al. [83] investigated the effects of different bridge structure types on performance, maintenance needs, and deterioration patterns. They integrate the structural type as a characteristic in neural network models, allowing for classification and comparative examination. The objective of these studies is to improve the comprehension of bridge deterioration by analyzing these elements and to create models and strategies for evaluating, predicting, and optimizing the conditions of bridges.

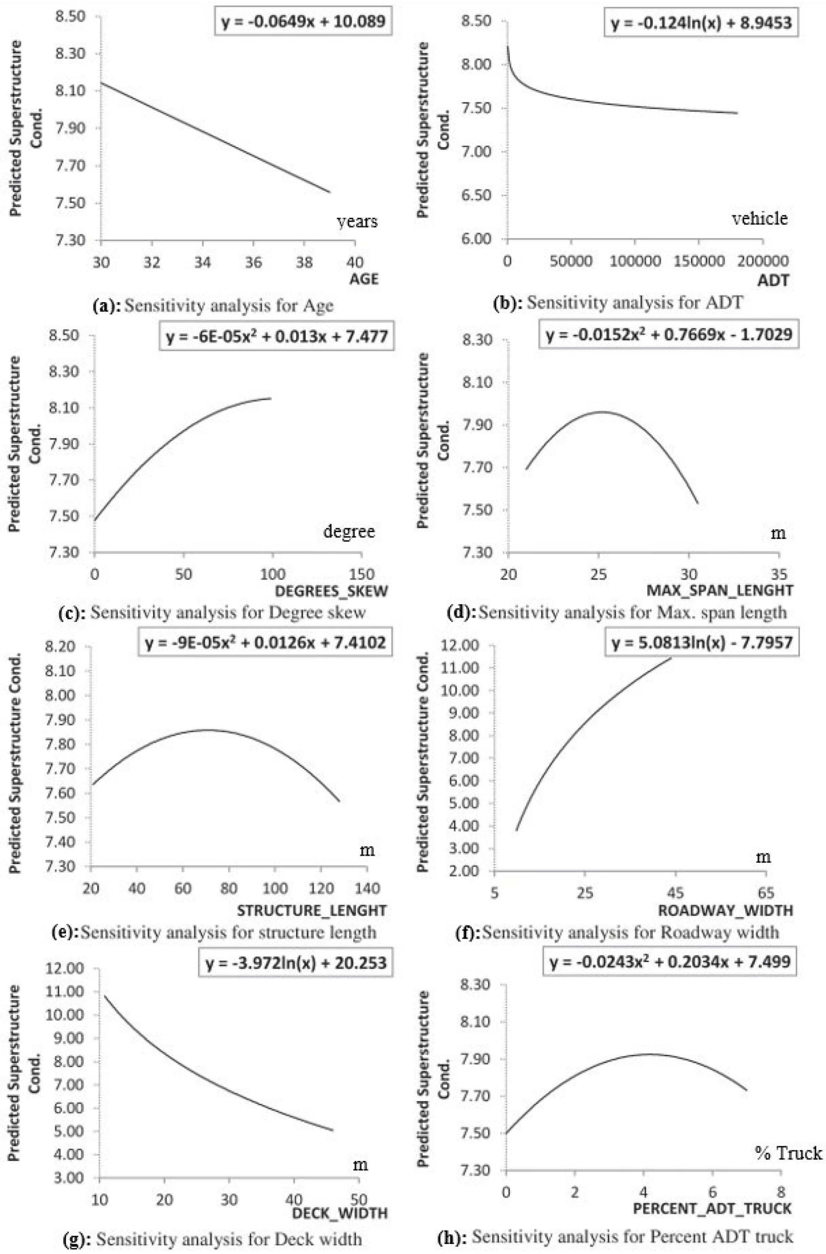

Figure 11. Sensitivity analysis for variables affecting predicted bridge superstructure condition (Reproduced from Ref. [86] Copyright (2019) Taylor & Francis).

Skewness is an essential determinant in bridge design, denoting the angle formed by the pier's centreline and a line perpendicular to the roadway's centreline. A thorough examination was undertaken by Hasan and Elwakil [40] to determine how skewness affects the deck condition rating of prestressed concrete bridges. By employing stochastic analysis and regression, they identified an inverse relationship between deck condition and skewness; this suggests that condition ratings correspondingly decrease as skewness increases. This study contradicts Hasan and Elwakil [86], who presented an opposing view, as illustrated in Figure 11. This discovery underscores the criticality of skewness consideration in bridge design to guarantee the most favorable deck condition and overall structure performance. Furthermore, Hasan and Elwakil [40] assessed the impact of the maximum span length on the deck condition rating of bridges constructed with prestressed concrete. A positive correlation was observed, indicating that elevated condition ratings are associated with extended spans.

This underscores the importance of incorporating the utmost span length into bridge design to improve the deck's condition and the bridge's overall performance. The results of this study underscore the criticality of integrating pertinent design elements, including skewness and maximal span length, to guarantee bridges' enduring robustness and structural soundness.

As depicted in Figure 12, a literature review highlights various factors that influence the degradation of reinforced concrete bridges. Among these factors, "bridge length" is the most frequently mentioned factor, being discussed 25 times, representing 22.73% of the citations. Ranking second, both "bridge width" and "structure type" were cited an equal number of times, with 21 mentions each (19.10%) in the filtered papers. The "thickness of deck" factor was mentioned 18 times, accounting for 16.37% of the citations, while the "concrete cover" factor was mentioned 17 times, representing 15.46% of the citations. The "maximum span" factor was also mentioned 16 times, corresponding to 14.55% of the citations. The "skewness" factor followed with 11 mentions, representing 10.00% of the citations. The remaining factors were cited less frequently, with only less than 7 mentions, indicating a lower significance level. In total, the factors in this category were cited 158 times across the 110 papers, which exceeds 100% due to multiple mentions in some articles, representing comprehensive coverage of the topic.

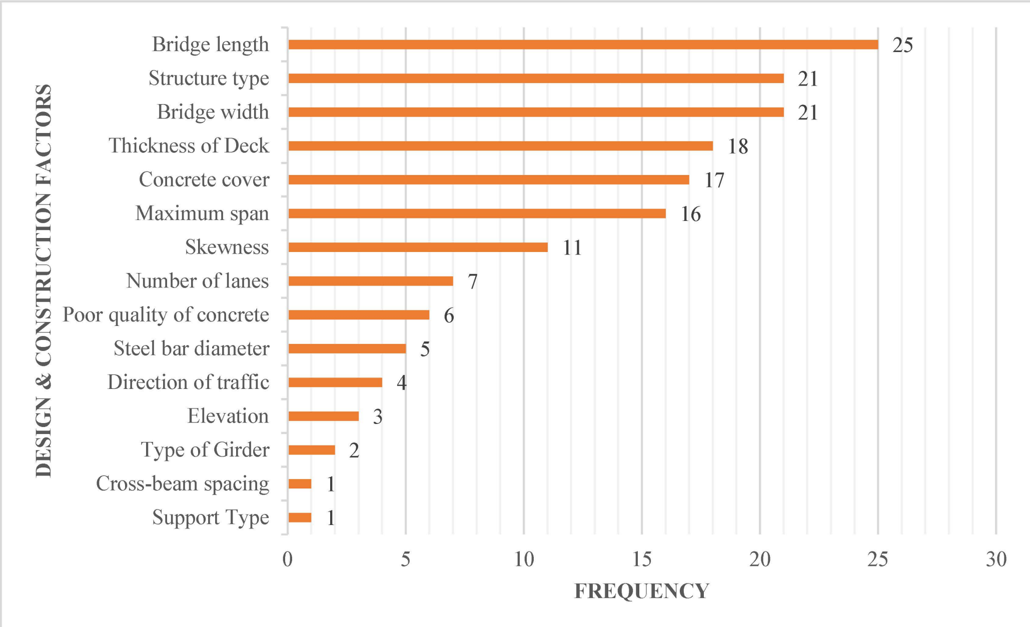

Figure 12. Bar chart for the design and construction category.

4.2.4. Physical Properties

Various physical factors can influence the deterioration of concrete bridge decks. These factors include bridge age (years in service), the distance from the coast, highway classification (whether in a rural or urban area), type of service on the bridge, and type of service under the bridge.

The impact of bridge age, represented by the BUILT_YEAR variable, on the prediction of bridge deck deterioration, has been investigated in multiple studies. In the random survival forest (RSF) model, it is commonly assumed that older bridges would undergo a faster deterioration process than newer ones. However, the feature importance analysis conducted on the RSF model suggests that the bridge age has a low ranking in determining the deterioration probability. This implies that the bridge age may not be a significant factor in predicting deterioration. The authors propose that this lack of significance could be attributed to the correlation between the bridge age and other attributes, such as rebar type, surface type, and district [87]. In contrast, the findings in Moomen and Siddiqui [88] reveal that the bridge age is statistically significant and positively contributes to the probability of the bridge components being in a poor condition while decreasing the likelihood of being in an excellent condition. The marginal effect analysis indicates that a one-year increase in bridge age raises the probability of being in poor condition by 0.14, 0.13, and 0.13 for the deck, superstructure, and substructure, respectively. Conversely, it decreases the likelihood of being in excellent condition by 0.12, 0.11, and 0.12, respectively. These results align with engineering intuition and previous studies, highlighting the importance of considering the bridge age in assessing deterioration. Due to the importance of bridge age as a vital influential factor in the deterioration process of bridge decks, it is incorporated as an input in many models, used to predict the deterioration of existing concrete bridges using a Long Short-Term Memory (LSTM) recurrent neural network and using the bridge age as one of the features to train the neural network models for condition assessment and prediction [83].

Coastal bridges are highly susceptible to concrete corrosion since they are located near the shoreline [89]. Recent research has highlighted the importance of this element in comprehending deterioration processes and enhancing maintenance procedures. In their study, Srikanth and Arockiasamy [3] employed a binary variable and Geographic Information System (GIS) to quantify the proximity of bridges to the coastline. This approach yielded valuable insights into the effects of such proximity on the deterioration of bridges. Similarly, Alogdianakis et al. [90] utilized Bayesian survival analysis to investigate the impact of closeness to seawater on the occurrence of corrosion and cracking in bridge decks. Their findings underscored the significance of factoring in this element when formulating plans for maintaining coastal bridges. Mascia and Sartorti [91] categorized bridges into 12 distinct categories according to their proximity to the coastline, spanning a range of 0 to 10 km inland. This range was considered appropriate for assessing the impact of airborne marine chlorides on bridge condition ratings. The study emphasized the substantial impact of proximity to the coastline on the accumulation of airborne sea chlorides, which can result in the erosion of structural steel and concrete. The researchers thoroughly examined the effects of airborne sea chlorides on bridge conditions by using accurate coastline and bridge coordinates. This study provided valuable insights for maintenance planning and measures to prevent corrosion.

The classification of a highway, whether in a rural or urban location, can contribute to the degradation of a concrete bridge deck. The relationship between highway classification and the degradation of a concrete bridge deck can be explained as follows. (1) Environmental Factors: Urban regions frequently experience elevated pollution levels because of intensified industrial operations and vehicular emissions. Chemical exposure to the bridge deck can cause the corrosion and degradation of the concrete over time. (2) Maintenance and Inspection: The categorization of the route might also impact the regularity and standard of maintenance and inspection endeavors. Urban highways are subject to more frequent inspections and maintenance because of their larger traffic volumes and greater significance in transportation networks. Regular maintenance and promptly addressing problems can effectively reduce the effects of deterioration and prolong the lifespan of the bridge deck. When evaluating the deterioration of a concrete bridge deck, it is crucial to consider the precise classification of the route. Engineers and maintenance experts can establish effective plans to monitor, maintain, and repair the bridge deck for long-term durability and safety by comprehending maintenance practices related to the highway classification [92]. The classification of highways is thought to influence the degradation of bridge decks, mainly because of differences in traffic and environmental conditions. To examine this theory, a study includes the functional class as a covariate in Bayesian survival analysis to quantify the impact of highway categorization on the Time to Initial Condition Rating (TICR) of bridge decks [90]. Moreover, the functional classification of highways significantly impacts the degradation of bridge decks by affecting variables such as traffic volume, load, and environmental conditions. The National Bridge Inventory (NBI) database's highway classification is converted into a binary system for an ANN model in a separate study. This conversion helps comprehend the influence of highway classification on bridge deck deterioration [93].

The type of service on a bridge refers to the capacity or workload that a system is designed to manage, which might have an impact on its rate of deterioration. The type of service is influenced by factors such as traffic volume, vehicle loads, and dynamic loads. The traffic volume of a bridge is determined by the total number of vehicles, including large ones such as trucks and buses, that pass over it. Vehicle loads refer to the combined weight of a vehicle, the arrangement of its axles, and the occurrence of vehicles exceeding weight limits. Dynamic loads encompass the forces generated by intense braking, acceleration, and vibrations resulting from rapid or fluctuating traffic conditions. Bridges subjected to high traffic volumes, frequent overloading, or substantial dynamic loads are more susceptible to accelerated deterioration, such as fatigue, cracking, and surface wear on the bridge deck [94]. The "type of service under the bridge" refers to the specific environmental conditions and infrastructure beneath the bridge deck that can impact its deterioration. Factors such as water exposure, moisture and humidity, chemical exposure, and vegetation and organic materials influence the service conditions. Water exposure is related to the presence of water bodies, like rivers or lakes, where the bridge spans and coastal bridges may encounter salt water. Moisture and humidity pertain to moisture in the soil or air beneath the bridge deck, which can cause corrosion and deterioration. Chemical exposure involves the presence of substances like industrial emissions or de-icing salts that can lead to a chemical attack on the bridge deck. Vegetation and organic matter refer to the growth of plants and the accumulation of organic materials below the bridge, promoting moisture retention and microbial activity that contribute to deterioration. The service conditions under the bridge can impact various deterioration mechanisms, including corrosion, alkali–silica reaction, or biological degradation, which can ultimately harm the long-term performance and durability of the bridge deck [95]. The type of service under and on a bridge has significant implications for various aspects of a research paper. Regarding bridge health monitoring, factors such as heavy traffic and corrosive environmental conditions can directly impact the bridge's health and structural integrity. Therefore, when researching bridge health monitoring, these factors should be considered in the objectives and methodology. Similarly, the services under and on the bridge are crucial for management and maintenance. Bridges with heavy traffic, for example, may require more frequent inspections and maintenance. Therefore, research papers aiming to develop intelligent bridge management and maintenance systems would consider these factors in their study. Furthermore, understanding the services under and on the bridge is essential in investigating bridge failures. By examining these factors, potential causes of bridge failures can be identified and analyzed. Overall, the type of service under and on the bridge is a critical consideration in the research objectives and methodology, influencing study design, data collection methods, and result interpretation [18].

Considering these physical factors is crucial in developing effective maintenance and preservation strategies to ensure concrete bridge decks' longevity and structural integrity. The "Bridge age (years in service)" factor emerged as this category's most frequently cited factor. It was mentioned 36 times in the database, accounting for 32.73% of the citations. Following this factor, "Highway classification" and "Distance from the coast" ranked second and third, respectively. They were cited 11 times (10.00%) and seven times (6.37%) in the filtered papers, respectively. The remaining factors, namely "Type of service under the bridge" and "Type of service on the bridge", were cited less frequently. They were mentioned 11 times, with "Type of service under the bridge" being cited six times and "Type of service on the bridge" being cited five times. Overall, the factors in this category were mentioned 65 times across the 110 papers, representing 59.11% of the total citations. Figure 13 illustrates physical properties, category-based factors, and related frequencies.

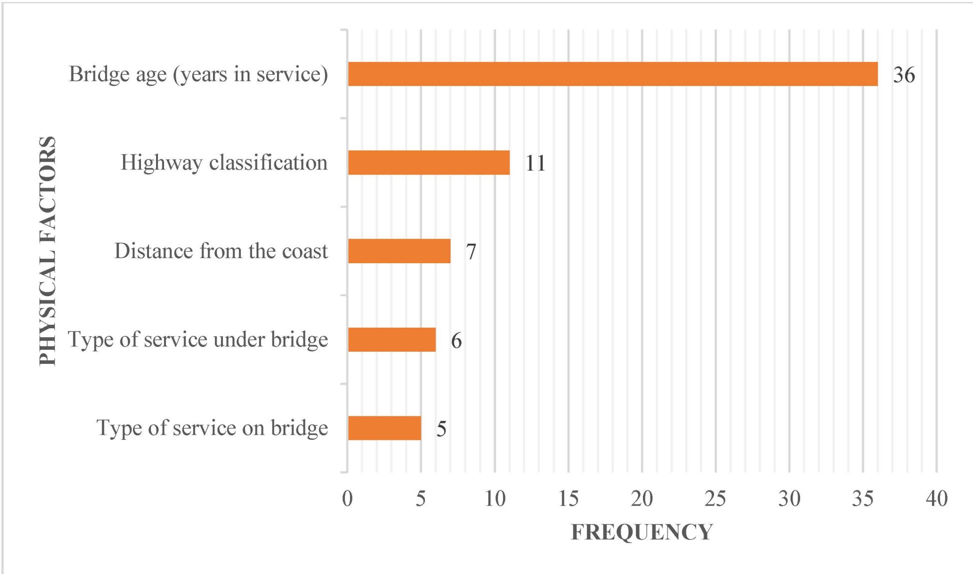

Figure 13. Bar chart for the physical properties.

4.2.5. Operational

The operational aspects leading to the deterioration of the bridge go along with the bridge life cycle, and both (deterioration and operation) affect each other, i.e., operational factors cause deterioration in the structure, whereas deteriorated surface affects the operational aspects [96,97]. This study identified six probable factors under the operational category that may lead to structural deterioration on the bridge deck, as shown in Table 4. As already discussed, each factor has been calculated for its weight percentage based on its frequency of appearance in the collected literature. In this category, "average daily traffic (ADT)" has been estimated as the most weighted percentage (43.64%). The ADT is the most crucial and important factor contributing to the direct deterioration of the bridge structure as the bridge deck surface transmits the traffic load on supporting/foundation elements of the bridge. The degradation process of the bridge deck is more rapid compared to other structural elements; thus, the ADT affects the durability of the bridge structure [98]. Following this, the "average daily truck traffic (ADTT)" (weighted percentage = 16.37%) also highly impacts structural health. It can be observed that for trucks, reinforced pavements are encouraged rather than bituminous wearing surfaces due to low condition ratings for bridge decks in the absence of deck reinforcements or deck membrane, irrespective of the ADTT [99]. Besides the aforementioned discussed factors, timely inspection and maintenance also play a role in increasing the life of a structure. Thus, a lack of "maintenance actions for superstructure, substructure, & deck" (weighted percentage = 12.73%) may lead to the early deterioration of the bridge. This is linked with the frequency and precision of "inspections" (weighted percentage = 3.64%). The inspection report will decide whether maintenance is necessary or if there is a need for inspection cycles in the future, as it includes detailed information about the issues causing bridge degradation, mitigation actions, and related attributes [100]. Although maintenance has financial impacts, and as per one study, in the life span of a bridge, the service/maintenance phase accounts for 88–92% and constitutes a major portion of the overall cost [101]. However, inadequate inspection and maintenance may lead to bridge failure [101]. There is one more factor, i.e., "drainage leakage" (weighted percentage = 5.46%), which is usually ignored, but it gradually degrades the structural condition and, if not controlled in a short time; otherwise, such leakage may lead to massive corrosion and deterioration. Expansion joints and drainage systems mostly cause leakages in bridges. Such leakages may lead to spalling in concrete structures, extreme corrosion, and various complex issues in bridge components. The leakage may transfer dirty water and salts, which may fuel the corrosive process in the bridge. Moreover, water leakage may also increase the impact of the freezing and thawing process during weather changes, thus damaging the bridge structure [102,103]. This study also identified a very rarely considered but extremely important factor under the operational category, i.e., "future average daily traffic", with a weighted percentage of 0.91%. Future estimation and reliable predictive calculations regarding ADT will help in the preservation of infrastructures, and deterioration impacts can be reduced accordingly [104]. Figure 14 illustrates operational category-based factors and related frequencies.

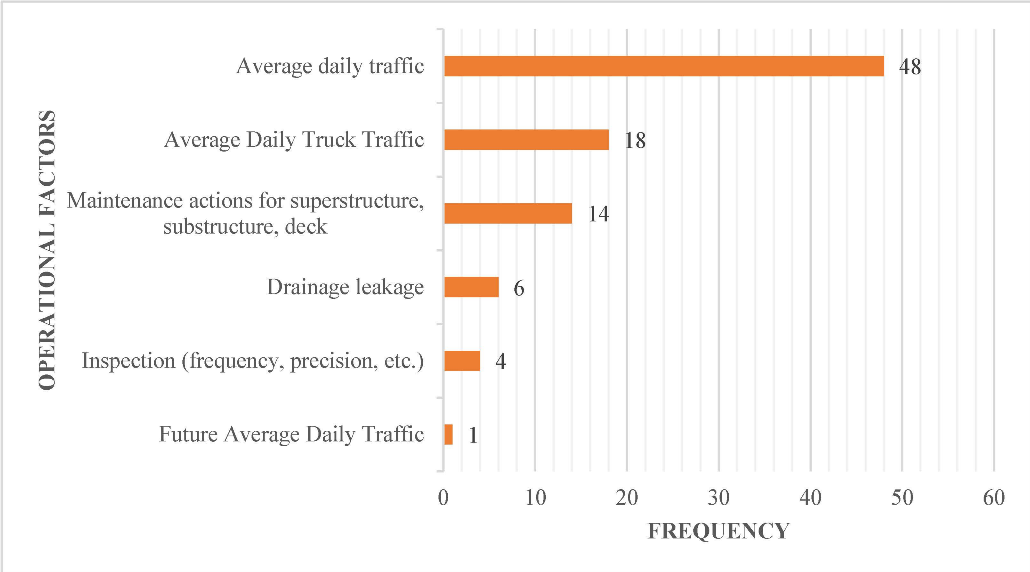

Figure 14. Bar chart for the operational category.

4.2.6. Environmental

The environmental factors affect the bridge condition by influencing the bridge properties, and it is noteworthy that environmental effects can be severe. However, environmental stressors are usually considered to affect the durability and strength of the bridge structure slowly and over time [105,106]. This study identified 12 factors under the environmental category. "Temperature" has been identified as the high-rated factor in this category, with a weightage percentage of 20.91%. The temperature plays a pivotal role in altering the bridge material's properties, such as boundary conditions, structural geometry, and elastic modulus of concrete. Moreover, it alters the axial force of the bridge, affecting the moving load-induced response [107]. The other factor is "freeze & thaw cycles" (weighted percentage = 19.10%), which is linked with temperature, especially cold weather. The freeze and thaw cycles adversely affect the impermeability and frost resistance of concrete structures, thus reducing the concrete's durability [108]. In contrast, too much "dry weather" (weightage percentage = 2.73%) also adversely affects the structural performance of the bridge by inducing thermal stresses, autogenous shrinkage, and drying shrinkage. These are followed by "humidity" and "precipitation", having the same percentage weightage as 15.46%. The literature reveals that humidity is a liable factor for the reduction in the service life of the bridge structure of approximately up to 10 years [109]. Likewise, a higher annual precipitation rate also affects the bridge's structural performance [110]. Moreover, both humidity and precipitation trigger corrosion phenomena [111]. Linked with the last two factors is "moisture content/variation", with a weightage percentage of 10.00%. The presence of excessive moisture affects the bondage in concrete, reducing the strength of the structure element, and, most of all, the penetration of excessive moisture into the bridge decks rated damages to the structure during freezing-thawing [112]. Other than these, "snowfall" has also been identified as a potential factor (weighted percentage = 6.37%) triggering the phenomenon leading towards the deterioration of bridge structure. Effects of most of these factors are interlinked under the same category, and they become potential reasons for other various actions resulting in the triggering of deterioration phenomena, such as the de-icing of snow salts, which are the probable causes of corrosion [113].

This study also explored the broad and widened prospects for identifying factors dealing with the deterioration of the bridge structure and identified the "scouring" process (weighted percentage = 4.55%) in critical bridges as a potential factor gradually leading toward structure deterioration, damage, and collapse [114]. However, the impact of scouring is dependent on foundation type/properties, type of river and stream, etc. [102]. Likewise, another factor that is fairly linked with scouring is "settlement" (weighted percentage = 3.64%); however, there may be other causes of settlement as well. Basically, settlement can be either due to the erosion of the foundation undersoil (which may be due to scouring) or due to a loss of water content from the soil, making it loose [115]. Other phenomena that may contribute to the settlement process are the dynamic and high-impact varying forces, leading to differential settlement [116]. Furthermore, "wind activity" (weighted percentage = 1.82%) has been identified as another factor directly or indirectly affecting the bridge's structural health. Very few studies took wind load/speed as a variable/parameter while determining the deterioration models for bridges [117]; however, the main reason for considering wind activity as a deterioration factor is the carrying and deposition of airborne chlorides and salts, especially near coastlines, that penetrate the concrete. The literature indicates wind's speed over 3 m/s as an effective speed to carry sea salts [118]. In the same way, the literature also highlights "pollution" (weighted percentage = 1.82%) as a triggering factor towards bridge deterioration, consisting of every type of pollution of land, water, and atmosphere. One of the least considered factors for the deterioration of bridge structures is "vegetation" (weighted percentage = 0.91%). Vegetation growing on the bridge structural elements produces cracks on the surface and becomes a source/trigger of various other deterioration phenomena [119]. Figure 15 illustrates environmental category-based factors and related frequencies. Figure 16 shows leakages at the bridge's joints caused by rainfall. Additionally, the moisture trapped in the concrete leads to vegetation growth.

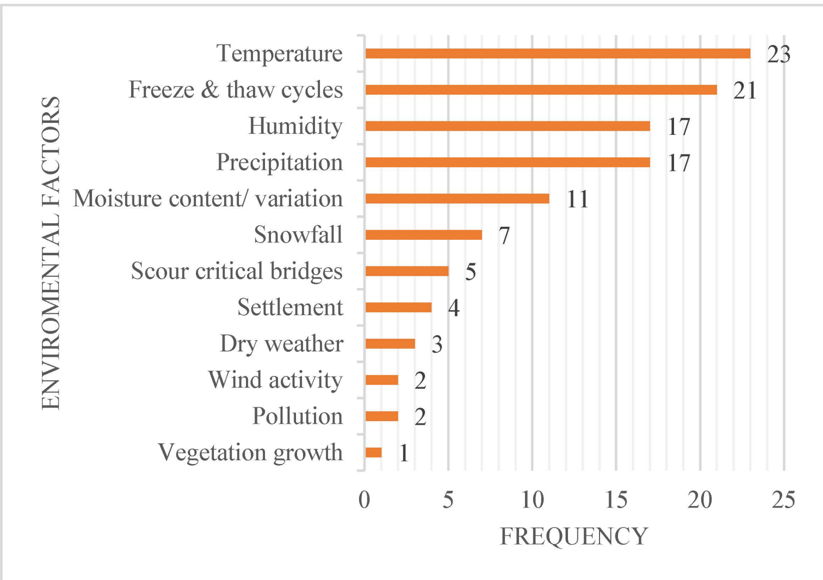

Figure 15. Bar chart for the environmental category.

Figure 16. Deterioration at the bridge joints caused by rain and vegetation.

4.2.7. Force Majeure

This study establishes force majeure as a category related to the deterioration factors for the bridge structure. Three main factors have been identified under it: "natural disaster (earthquake, typhoon, flood, etc.)", "war/bomb damage", and "fire", with weightage percentages of 6.37%, 1.82%, and 0.91%, respectively. Following the performed review for this study, other authors have identified natural catastrophes (earthquakes, typhoons, floods, etc.) as significant events that, whether occurring suddenly or progressively, impair and compromise structural integrity [120,121]. The extent of damage and deterioration is dependent on the intensity/amplitude of the natural disaster and the age of the structure [5,122]. Furthermore, events such as warfare, bomb damage, or terrorist acts may compromise the building, resulting in structural breakdown [123,124]. On the other hand, structural steel elements are mostly fireproofed; however, fire incidents create temperature variations that cause thermal cracking in concrete elements. The fire heat evaporates the pore water, causing contraction in the cement paste, and aggregate in the concrete undergoes progressive expansion, rupturing the surface. Though fire mostly damages the exposed part of the structure, fire causes spalling and random interlinked cracks, which overall affects the strength of the structural elements. The literature reveals that fire heat under 250 °C does not necessarily cause significant cracking [125,126]. Although the occurrences of force majeure factors are very rare and unpredictable, the impact is extreme towards deterioration, which may lead to structural collapse or failure. Moreover, the factors defined under the force majeure category may trigger and fuel other categories of deterioration factors, which can slowly lead to structural failure [114]. Figure 17 illustrates force majeure category-based factors and related frequencies.

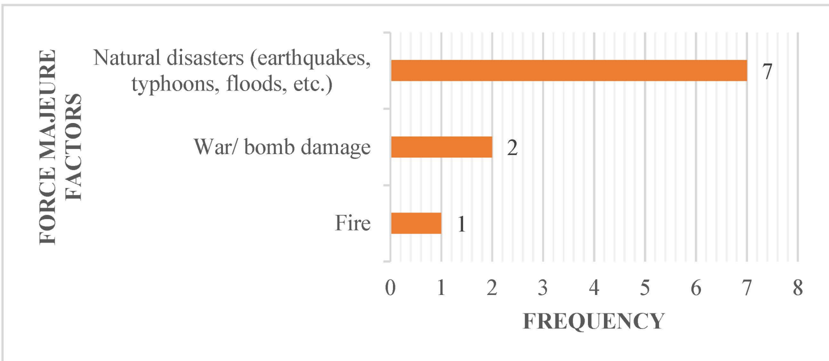

Figure 17. Bar chart for the force majeure category.

5. Research Gaps and Future Directions

This study has successfully identified a comprehensive set of 54 critical deterioration factors categorized into seven distinct categories for concrete bridge structures. These factors have been extracted from various deterioration model-based studies on concrete bridges, utilizing a systematic data collection approach and scientometric analysis. The primary objective of this study was to compile and present a maximum number of critical deterioration factors sourced from the existing literature. The findings of this study provide valuable insights and resources for both practitioners and researchers in the field, facilitating a better understanding of the factors influencing the deterioration of concrete bridge structures.

It is important to note that when considering the critical deterioration factors for a specific region, factors should be assessed based on the region's unique conditions, including weather patterns (meteorological data) and traffic conditions throughout the year. The impact of certain factors may vary depending on these aspects. For instance, in Hong Kong, factors such as snowfall, dry weather, freeze and thaw cycles, and de-icing with salts/chloride would have no impact and can be disregarded, whereas in regions like Canada or the United States of America, where regular snowfall occurs, these factors become relevant. In Hong Kong, factors such as humidity, precipitation, wind activity, and natural disasters (e.g., typhoons) would be considered more impactful based on historical meteorological records. This study has extracted deterioration factors from the literature, specifically deterioration models, and categorized them accordingly. The factors have been generically ranked based on their frequencies. Within each category, two types of critical deterioration factors have been collected: generic factors that are applicable in all conditions regardless of the region and specific factors that may vary based on the region's meteorological conditions and traffic model. Therefore, it is essential for researchers and practitioners to consider the impacts of these factors based on the specific region where the implementation takes place.

Considering previous research studies, it is evident that most of the developed deterioration models heavily rely on visual inspection records to examine the relationship between input deterioration factors and the future condition of bridge components. However, visual-based inspection is subjective, intuitive, and prone to inaccuracies. Consequently, there is a notable lack of non-destructive evaluation-based deterioration models that can provide accurate defect-based evaluations of bridge components. Another notable observation is the limited research efforts dedicated to the hybridization of different types of deterioration models. For instance, there is a lack of studies that explore the combination of mechanistic and stochastic models or the integration of mechanistic models with artificial intelligence techniques. These hybrid models hold significant value as they enable the capturing of the actual deterioration mechanisms and facilitate accurate assessments of their impact on the lifecycle performance of bridges. Further research in this area is crucial to enhance the effectiveness and reliability of deterioration modeling in bridge engineering.

Furthermore, there is a dearth of studies in the literature regarding the weighting and prioritization of deterioration factors, indicating a gap in understanding the importance and relative influence of these factors. Moreover, previous studies have shown a lack of research specifically focused on deterioration factors affecting concrete bridge decks in developing countries. Adding to these shortcomings is the scarcity of publicly available datasets, such as national bridge inventories, which are crucial for enriching and advancing state-of-the-art deterioration models. These datasets play a pivotal role in establishing a comprehensive understanding of nature and factors contributing to bridge deterioration.

As shown in Figure 18, recognizing the existing gaps in the field of deterioration modeling for bridge components, it is crucial to undertake further research to address these limitations. Key areas for future investigation include the following.

1. Development of Non-Destructive Evaluation-Based Models. There is a pressing need to develop robust deterioration models that rely on non-destructive evaluation techniques. By moving beyond subjective visual inspection records, these models can provide more accurate defect-based evaluations of bridge components, enhancing the reliability of predictions.
2. Exploration of Hybrid Models. Efforts should be directed towards hybridizing different modeling approaches, such as combining mechanistic and stochastic models or incorporating artificial intelligence techniques. These hybrid models have the po-

tential to capture the intricate deterioration mechanisms and accurately assess their impact on the lifecycle performance of bridges.

3. Weighting and Prioritization of Deterioration Factors. Further studies are required to investigate the relative importance and influence of different deterioration factors. Understanding the weighting and prioritization of these factors will aid in developing more comprehensive deterioration models and prioritizing maintenance and repair interventions effectively.
4. Specific Studies on Concrete Bridge Decks in Developing Countries. The literature currently lacks sufficient research focused on deterioration factors affecting concrete bridge decks in developing countries. It is essential to conduct targeted studies in these regions to gain insights into the unique challenges and develop context-specific deterioration models.
5. Collection and Sharing of Publicly Available Datasets. To advance state-of-the-art deterioration modeling, efforts should be made to collect and share publicly available datasets, such as national bridge inventories. These datasets are invaluable for enriching the accuracy and effectiveness of deterioration models, enabling a more comprehensive understanding of nature and contributing factors of bridge deterioration.

By addressing these research gaps, the field of deterioration modeling can make significant strides toward enhancing the management and maintenance of bridge infrastructure, leading to improved safety, sustainability, and cost-effectiveness.

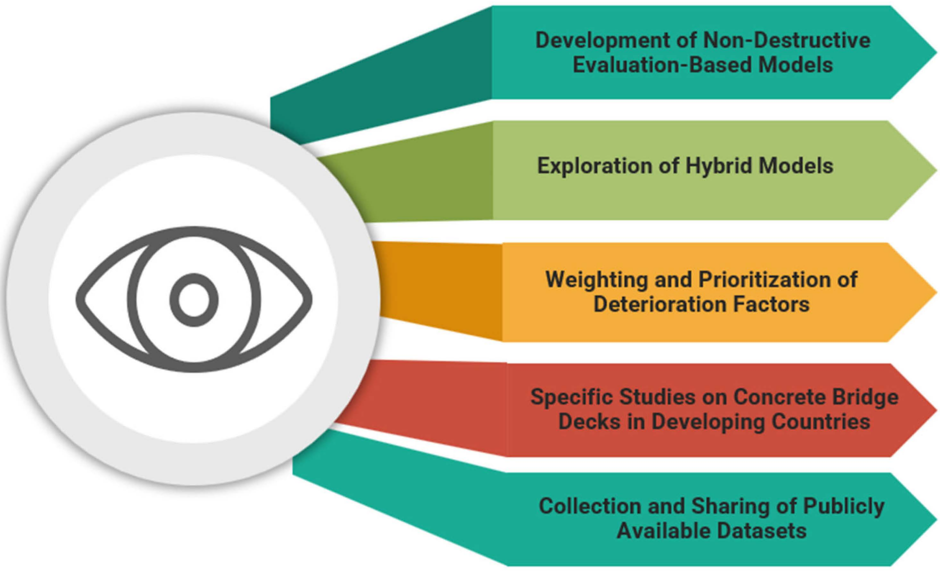

Figure 18. Gaps in the Literature on Concrete Bridge Deck Deterioration Models and Factors.

6. Conclusions

It is crucial to identify and manage the factors contributing to bridge deterioration to ensure effective maintenance beyond simply repairing damage. Understanding these factors aids in analyzing cause and effect, diagnosing issues, and modeling bridge deteriorations. This, in turn, enhances the accuracy of predictions and helps minimize overall costs throughout the bridge's lifespan. Hence, the aim of this research was to review the factors contributing to the deterioration of concrete bridges and examine the existing deterioration models used for predicting the conditions of these bridges. To achieve this, a mixed methodology approach combining scientometric and systematic analyses was adopted. The analyzed database consisted of 331 documents. The systematic analysis conducted in this research was divided into two parts: the analysis of deterioration models and the examination of linked deterioration factors. In the first part, the analysis revealed that a total of 54 factors were cited in the literature as significant contributors to the deterioration of concrete bridges. These factors were further categorized into seven groups based on their nature and characteristics. At the group level, the most frequently cited deterioration factors were as follows: “material type” in the “material properties” group, “de-icing with salts/chloride” in the “chemical” group, “bridge length” in the “design & construction” group, “bridge age” in the “physical” group, “average daily traffic” in the “operational” group, “temperature” in the “environmental” group, and “natural disasters” in the “force majeure” group. Overall, “de-icing with salts/chloride” was the most cited factor, appearing in 52 studies, followed by “average daily traffic” with 48 citations and “bridge age” with 36. The “chemical” group had the highest average citations per factor (17), with “operational” factors averaging 15.17 and “physical” factors close behind.

In summary, this paper compiles a comprehensive list of deterioration factors identified in the literature, categorizing and ranking them according to their frequency of citation. While this provides valuable insight into the most commonly reported causes of concrete bridge deteriorations, it is essential to account for region-specific conditions, such as local climate patterns, seasonal meteorological changes, and traffic fluctuations throughout the year. These factors can significantly influence the rate and severity of deterioration and may vary widely across different geographic regions. Therefore, developing deterioration models tailored to specific environmental and operational contexts is critical for more accurate predictions and effective maintenance strategies. Additionally, addressing the gaps in deterioration modeling for bridge components is vital for improving maintenance strategies. Future research should prioritize the development of non-destructive evaluation-based models to enhance prediction reliability beyond visual inspections. Furthermore, exploring hybrid models that combine mechanistic, stochastic, and artificial intelligence techniques can better capture complex deterioration mechanisms. It is essential to investigate the weighting and prioritization of deterioration factors and conduct specific studies on concrete bridge decks in developing countries where research is currently insufficient. Lastly, collecting and sharing publicly available datasets, such as national bridge inventories, will enrich the understanding of bridge deterioration. By focusing on these areas, we can significantly advance the field and enhance bridge maintenance practices.

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Abbreviations

ACR	alkali-carbonate reaction
ADT	average daily traffic
ADTT	average daily truck traffic
AI	artificial-intelligence
ANN	artificial neural network
APR	annual publication rate
ASR	alkali-silica reaction
$b^{(L)}$	bias vector for layer L
BML	Bayesian maximum likelihood
C_d	condition stage of the bridge
CEM	construction engineering and management
CPM	capital preventative maintenance
DET_FMB	deterioration factors and models of bridges
DLA	diffusion-limited aggregation
DLNN	deep learning neural networks
DNN	deep neural network
DT	decision trees
F	constant value
f	activation function

GIS	Geographic Information System
I	corrosion product
k	deterioration constant
KNN	K-nearest neighbors
LR	linear regression
m	number of electrons transferred
M_d	mass of corrosion product
MR&R	maintenance, repair, and replacement
n	sensitivity of deterioration to the condition state
NLO	nonlinear optimization
OPM	ordered probit modeling
PHM	proportional hazards-based modelling
PNBM	Poisson and negative binomial-based modeling
RF	random forest
RSF	random survival forest
SLR	systematic literature review
t_d	deterioration time
v	volatility
TICR	time to initial condition rating
$W_d(t)$	wiener process
$W^{(L)}$	weight matrix for layer L
WoS	Web of Science
y_i	actual condition index
$\tilde{y}_i$	predicted condition index
YR	publication year under
μ	drift coefficient
σ	stress

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