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Dedication

It is our pleasure and great privilege to present the 80th issue of the Academic Journal of Research and Scientific Publishing to all researchers and professor who published their research in the issue, and we thank and appreciate to all contributors and supporters of the academic journal and those involved in the production of this scientific knowledge edifice.

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Application of Artificial Neural Networks for Predicting the Structural Number of Flexible Pavements Based on Subgrade Soil Properties

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Abstract:

The structural number (SN) is a critical parameter in the AASHTO design method, representing the overall load-bearing capacity of flexible pavements. Traditional determination of SN requires resilient modulus (MR) and California Bearing Ratio (CBR) tests, which are both costly and time consuming. This study proposes an artificial neural network (ANN) model as an alternative approach for predicting SN using readily available subgrade soil properties and environmental factors. A dataset of 2,810 samples was compiled and preprocessed, with dry unit weight (γd), moisture content (w), weighted plasticity index (wPI), and number of freeze–thaw cycles (NFT) employed as model inputs. The ANN was developed in MATLAB using a feed-forward architecture with a single hidden layer of 10 neurons and trained with the Levenberg–Marquardt algorithm. Model performance was evaluated using mean squared error (MSE) and correlation coefficient (R). The results showed strong predictive capability, with R values of 0.954, 0.948, 0.942, and 0.951 for training, validation, testing, and overall datasets, respectively. Error histograms and regression plots confirmed the model's robustness and generalization capacity. The proposed ANN framework provides a reliable and cost-effective tool for estimating SN, reducing dependence on expensive laboratory testing while supporting efficient and accurate pavement design.

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Keywords: Artificial neural networks (ANNs), flexible pavement design, structural number (SN), subgrade soil properties, machine learning in transportation engineering.

1. Introduction

The design of flexible pavements plays a critical role in ensuring long term performance, safety, and cost efficiency in transportation infrastructure. Among the various methodologies developed, the American Association of State Highway and Transportation Officials (AASHTO) design method for flexible pavements remains one of the most widely adopted systems worldwide. The 1993 AASHTO Guide for the Design of Pavement Structures incorporates multiple factors such as traffic loading, material properties, drainage, environmental conditions, and reliability to determine the required pavement strength (AASHTO, 1993). Central to this design framework is the structural number (SN), which quantifies the overall load carrying capacity of a pavement. The SN is subsequently translated into pavement layer thicknesses through layer coefficients that represent the relative contribution of asphalt, base, and subbase materials (Abaza & Abu-Eisheh, 2003).

Despite its robustness, the AASHTO design method relies heavily on parameters such as the resilient modulus (MR) and the California Bearing Ratio (CBR) of the subgrade soil. However, determining these parameters through laboratory testing is both expensive and time-consuming, often requiring specialized equipment and controlled testing conditions. Consequently, these tests are not always practical or feasible in routine pavement design projects, especially in regions with limited laboratory resources or time constraints.

Nevertheless, many researchers continue to employ traditional pavement design methods that depend on these parameters. In such studies, the resilient modulus of the subgrade is either measured directly through repeated load triaxial testing or estimated indirectly by converting CBR values to equivalent MR values. These parameters are then used as key geotechnical inputs for the characterization of the subgrade, base, and subbase layers (Jain et al., 2013; Kumar et al., 2020; Mendoza-Sanchez et al., 2024; Pranay Kumar et al., 2018; Ziar et al., 2023)

Due to the economic and logistical challenges associated with MR and CBR testing, researchers have increasingly explored alternative methods for predicting pavement strength using readily available soil index properties and environmental factors.

Among these researchers, the first alternative solution to this problem was proposed by Ziar (2025), who utilized four machine learning algorithms to predict the structural number of flexible pavements based on the subgrade soil's index properties (Ziar, 2025).

On the other hand, several studies have focused on the effective structural number (SNeff), which represents the remaining structural capacity of a pavement during its service life. For instance, Karballaeezadeh et al. (2020) employed various machine learning models—such as Gaussian process regression, model trees, and random forests—to estimate SNeff from pavement deflection and temperature data (Karballaeezadeh et al., 2020). Similarly, Abd El-Raof et al. (2020) enhanced structural number prediction models by incorporating temperature correction factors into Long-Term Pavement Performance (LTPP) datasets (Abd El-Raof et al., 2020).

These studies demonstrate the growing potential of data-driven approaches in pavement engineering. However, most existing research has primarily focused on pavement evaluation and performance monitoring, rather than addressing the initial design stage of pavement systems.

The present study addresses this gap by developing an artificial neural network (ANN) based model for predicting the initial structural number (SN) of flexible pavements at the design phase. Unlike previous work on SNeff, this research emphasizes the estimation of SN prior to degradation, ensuring accurate thickness design from the outset. The ANN model eliminates the reliance on costly MR and CBR tests by utilizing easily measurable subgrade soil properties such as dry unit weight (γd), moisture content (w), and weighted plasticity index (wPI) along with the number of freeze thaw cycles (NFT) as an environmental factor.

By leveraging the learning capacity of artificial neural networks, this study aims to provide a reliable, efficient, and cost-effective prediction framework for flexible pavement design. The proposed approach contributes not only to reducing design costs and testing requirements but also to advancing the integration of artificial intelligence in pavement engineering practice.

2. Research Methodology

The primary objective of this study is to develop and evaluate an artificial neural network (ANN) model for predicting the structural number of flexible pavements at the design stage. This research also aims to demonstrate the applicability of ANN as a robust alternative to traditional laboratory-based methods, thereby supporting future studies in integrating advanced artificial intelligence techniques into the design of both flexible and rigid pavements.

To achieve this, the SN was predicted using fundamental subgrade soil properties, namely dry unit weight (γd), moisture content (w), and the weighted plasticity index (wPI), which is defined as the product of the percentage passing through the No. 200 sieve and the plasticity index

(Kardani et al., 2022). In addition, environmental conditions exert a substantial influence on pavement behavior and longevity. Variations in climate directly affect how quickly pavements deteriorate, thereby impacting maintenance requirements and overall lifecycle expenditures (Mendoza-Sanchez et al., 2024; Qiao et al., 2020; Zapata et al., 2007). The environmental influences governing pavement response can generally be grouped into external and internal factors. External influences include climatic and hydrological elements such as temperature changes, rainfall, groundwater fluctuations, and freeze–thaw activity. Internal factors, by contrast, are related to the in-situ conditions within the pavement system, including moisture migration, drainage capacity, and water infiltration between structural layers (Zapata et al., 2007).

Among these environmental factors, the number of freeze–thaw cycles (NFT) was specifically included as a variable in this study, as it represents a key indicator of cyclic freezing and thawing effects on pavement materials. These cycles induce volumetric changes, often leading to cracking, loss of stiffness, and accelerated structural degradation, particularly in regions with severe seasonal temperature variations (Jafari & Lajevardi, 2022; Su et al., 2017; Zou et al., 2021). Including NFT as a variable allows the model to account for the environmental impact on pavement performance alongside fundamental soil properties. These input features were utilized in the ANN prediction model, as detailed in the dataset description and preprocessing sections.

The dataset employed for this study consists of 2,810 data points. The data were preprocessed and divided randomly into three subsets: 70% (1,966 data points) for training, 15% (422 data points) for validation, and 15% (422 data points) for testing. The ANN was implemented using MATLAB R2024b's neural network fitting toolbox with a feedforward architecture comprising a single hidden layer of 10 neurons. The Levenberg–Marquardt backpropagation algorithm was adopted as the training algorithm, with mean squared error (MSE) selected as the performance function. The creation and development of the model are discussed in detail in the subsequent sections following the data description and preprocessing.

2.1. Data Collection and Preparation

The dataset applied in this research was first assembled and made publicly available by Zou et al., (2021) as supplementary material to their publication (Zou et al., 2021). It contains experimental outcomes of resilient modulus (MR) tests on compacted subgrade soils, which were classified under both the AASHTO system (A-4, A-6, and A-7-6) and the Unified Soil Classification System (USCS) (CL, CH, and CL-ML). The dataset was downloaded directly from the supplementary files provided by the publisher. The compiled database integrates results reported in several prior studies, including those of (Ding et al., 2020; Rahman, 2014; Ren et al., 2019; Solanki et al., 2013).

The principal input parameters considered in relation to MR include the weighted plasticity index (wPI), dry unit weight (γd, kN/m³), confining stress (σc, kPa), deviator stress (σd, kPa), number of freeze–thaw cycles (NFT), and moisture content (w, %). In their work, Zou et al. (2021) employed this dataset to construct prediction models based on gene expression programming (GEP) and artificial neural networks (ANNs), linking soil properties, stress conditions, and environmental effects to the resilient modulus of pavement subgrade soils (Zou et al., 2021).

In this study, instead of directly applying the dataset for resilient modulus prediction, it was reformulated to suit the specific goal of developing and evaluating an artificial neural network for predicting the total structural number of flexible pavements. The prediction framework was based on subgrade soil properties and environmental influences under a specified traffic level and fixed pavement design conditions. To achieve this, the original MR values were transformed into corresponding SN values using the bisection method, which iteratively solves the AASHTO 1993 pavement design equation. This equation defines the relationship between SN and a set of design parameters, including cumulative traffic loading (W18), reliability factor (ZR), overall standard deviation (So), serviceability loss (ΔPSI), and MR (AASHTO, 1993). For this study, the design inputs were adopted in line with the AASHTO 1993 Guide for Design of Pavement Structures, with W18 set to 5 million equivalent single axle loads (ESALs), a reliability level of 95% (ZR = –1.282), So fixed at 0.45, and ΔPSI taken as 2.5. The selection of these values provides a conservative but realistic representation of traffic, material, and construction variability.

The traffic loading of W18 = 5 million ESALs was chosen to reflect conditions typical of medium- to high-volume facilities such as major arterials and intercity corridors. The reliability level of 95% falls within the commonly applied range of 85–99.9% for critical highway systems (see Table (1)), thereby ensuring robustness against design uncertainties. While the AASHTO design guide recommends an initial serviceability index (Pi) of 4.2 and a terminal serviceability index (Pt) of 2.5 (ΔPSI = 1.7) (AASHTO, 1993), this study adopted a more conservative ΔPSI of 2.5 to reflect higher performance standards and stricter intervention thresholds. These parameter choices strengthen the analytical framework by aligning with accepted design practice while ensuring a resilient pavement structure.

In the AASHTO equation (see Equation (1)), W18, ZR, ΔPSI, So, and MR are treated as known parameters, whereas SN is the unknown to be determined. To calculate SN, an objective function was formulated as the difference between log10(W18) and the right-hand side of the equation. The bisection method, implemented in Python, was employed as a root-finding technique, iteratively refining the SN value until convergence was achieved within a tolerance of 0.001. This procedure was applied to all MR records in the dataset, resulting in a newly constructed database where SN served as the target output variable. The input features included weighted plasticity index (wPI), dry unit weight (γd, kN/m³), moisture content (w, %), and freeze–thaw cycles (NFT), which are recognized as key factors influencing MR and, consequently, SN. The statistical characteristics of these variables are presented in Table 2. This revised dataset was subsequently utilized for the development and training of the artificial neural network prediction model.

Fig. 1 illustrates the Pearson correlation heatmap showing the relationships between the input variables and the structural number (SN) of flexible pavements. Correlation coefficients range from −1 to +1, where positive values indicate direct relationships and negative values indicate inverse relationships. In the heatmap, yellow shades represent strong positive correlations, dark blue indicates strong negative correlations, and gray tones correspond to weak or near-zero correlations. Among the variables, moisture content (w) shows the strongest positive correlation with SN (r = 0.51), followed by NFT (r = 0.36), suggesting that both moisture and freeze–thaw cycles increase pavement thickness requirements. In contrast, dry unit weight (γd) exhibits a moderate negative correlation with SN (r = −0.35) and a strong inverse relationship with moisture content (r = −0.90), highlighting their interdependence. The weakest association is observed between wPI and SN (r = 0.12), indicating that wPI has a relatively limited direct influence on pavement design.

Fig. 2 presents histograms of wPI, γd, w, NFT, and SN, showing the frequency distribution of observations across their respective ranges. These plots provide insights into data spread, central tendency, and variability, while also revealing potential skewness, clustering patterns, or outliers.

$$\log_{10}(W_{18}) = Z_R S_o + 9.36\log_{10}(SN+1) - 0.20 + \frac{\log_{10}\left[\frac{\Delta PSI}{4.2-\Delta PSI}\right]}{0.40+\frac{1094}{(SN+1)^{5.19}}} + 2.32\log_{10}(MR) - 8.07 \quad (1)$$

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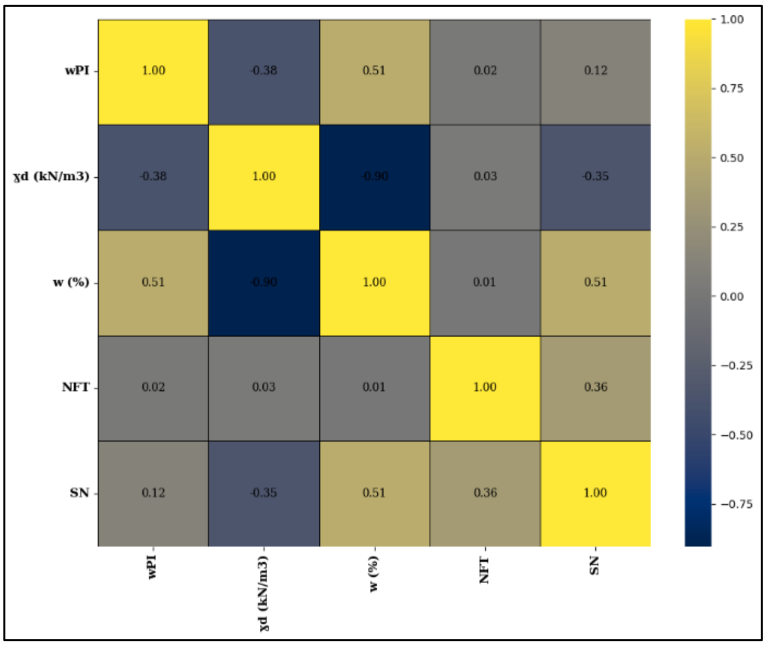
Table 1. Recommended reliability levels for different functional classifications(AASHTO, 1993)

Recommended Level of Reliability (%)		
Functional Classification	**Urban**	**Rural**
Interstate and other Freeways	85-99.9	80-99.9
Principal Arterials	80-99	75-95
Collectors	80-95	75-95
Local	50-80	50-80

Table 2. Summary statistics of input and output variables

Parameters	wPI	γ_d (kN/m^3)	w (%)	NFT	SN
Maximum	31.08	20.40	41.54	20.00	9.37
Minimum	5.82	15.50	12.30	0.00	2.53
Range	25.26	4.90	29.24	20.00	6.84
Mean	13.88	17.73	18.36	4.14	5.03
Median	13.16	17.77	17.30	3.00	5.08
Standard deviation	6.44	1.56	4.52	3.93	0.90

Fig 1. Pearson correlation heatmap of input variables and the structural number (SN). Yellow indicates strong positive correlations, dark blue indicates strong negative correlations, and gray represents weak or near-zero correlations.



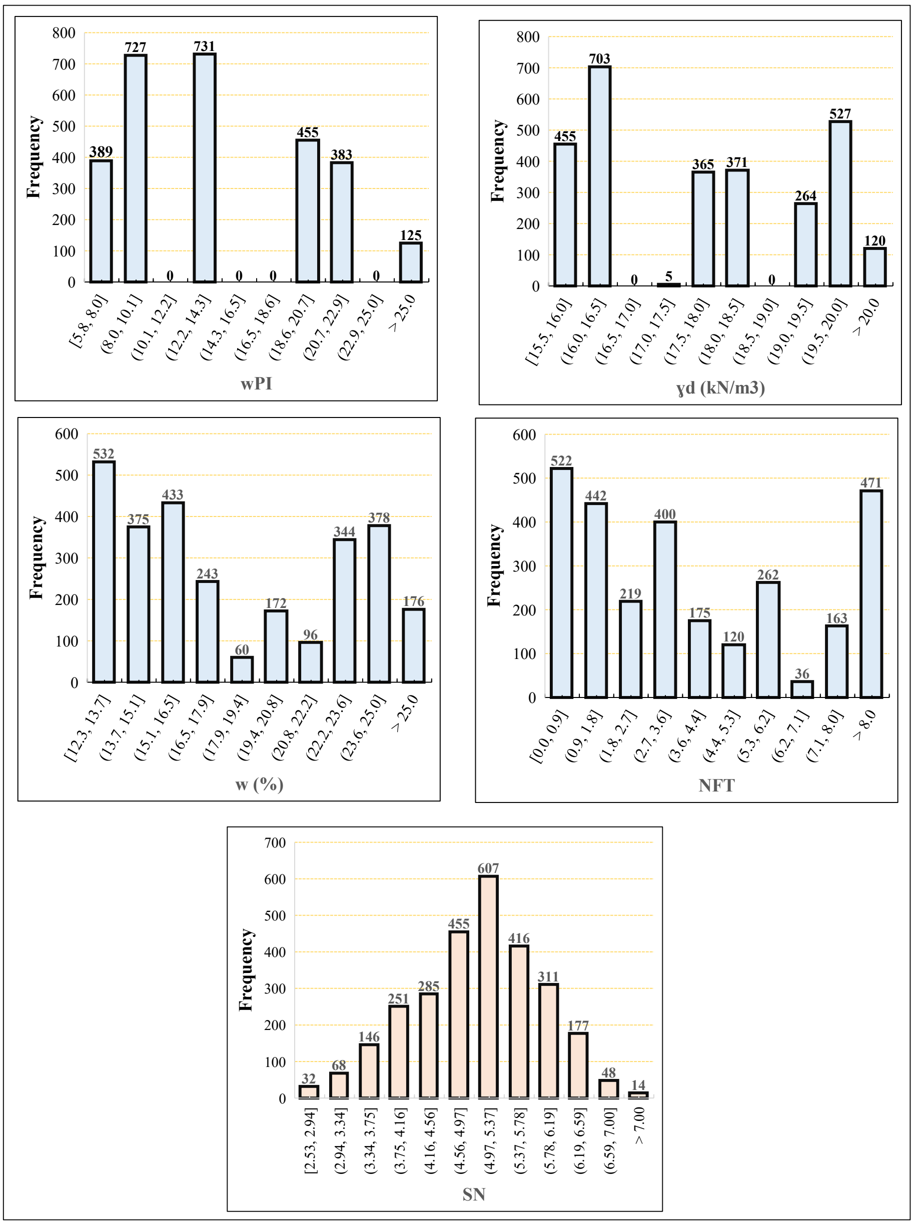


Fig 2. Histograms of wPI, γd, w, NFT, and SN showing the frequency distribution of observations. The plots highlight the spread, central tendency, and variability of the dataset, as well as potential skewness, clusters, or outliers.

2.2. Creation and Development of the ANN Model

The artificial neural network model in this study was developed and trained using the Levenberg–Marquardt algorithm due to its efficiency in handling nonlinear optimization problems. A feed-forward architecture was employed, consisting of an input layer, a hidden layer, and an output layer, with neurons interconnected through weights, biases, and activation functions (Arunvivek et al., 2025; Barkhordari et al., 2022; Khan et al., 2022; Li et al., 2023; Qi et al., 2023).

Each input node corresponded to an independent variable, ensuring comprehensive representation of the dataset and allowing the model to capture complex relationships among subgrade soil properties and environmental factors. To prevent overfitting and enhance computational efficiency, the architecture was kept simple with a single hidden layer, while the number of neurons was determined through experimental trials to achieve an optimal balance between learning capacity and generalization.

After testing several configurations, a hidden layer of 10 neurons demonstrated the best predictive performance. The network training was stopped once generalization was achieved, as indicated by increasing mean squared error (MSE) on the validation set.

Model performance was evaluated using correlation coefficients and error metrics such as MSE and ensuring reliable prediction of the target variable. The final ANN architecture and workflow are illustrated in Fig. 3. while the regression plots and performance indices, including training, validation and testing R-values, are presented in results and discussion section.

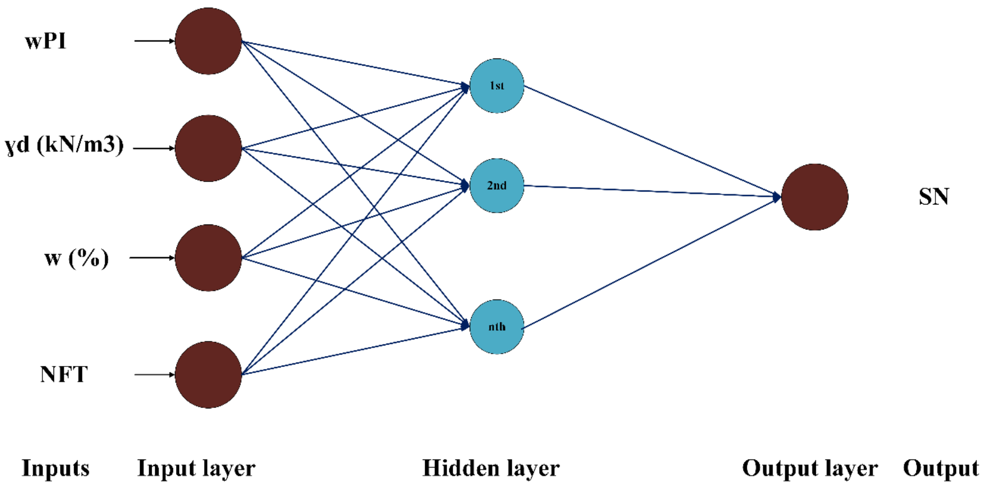


Fig 3. Architecture of the artificial neural network (ANN) model used in this study

3. Results and Discussion

To evaluate the predictive performance of the developed ANN, regression analyses were conducted for the training, validation, testing, and overall datasets (Fig. 4). The network achieved high coefficients of determination (R^2), with values of 0.951 for training, 0.948 for validation, 0.930 for testing, and 0.949 overall. The close agreement between predicted and actual values across all subsets indicates that the ANN effectively captured the nonlinear interactions among soil properties and environmental factors influencing the structural number. These findings confirm the robustness and reliability of the ANN as a predictive tool for flexible pavement design.

Model training performance is presented in Fig. 5, where the best validation performance was achieved at Epoch 114 with a minimum mean squared error (MSE) of 0.074116. Training was stopped automatically at this point to prevent overfitting. The convergence of the training, validation, and testing curves demonstrates that the network generalized effectively without significant loss of accuracy. The error distribution is shown in Fig. 6. Most residuals are concentrated around zero and exhibit a nearly symmetric pattern across the training, validation, and testing subsets. This distribution further supports the accuracy and stability of the ANN predictions.

The overall status of the network during training is summarized in Fig. 7, where the gradient, Mu, and validation checks were monitored over 120 epochs. The gradient decreased steadily and stabilized at 0.068 by the final epoch, indicating effective convergence of the optimization process. The parameter Mu, which regulates the adaptation of the Levenberg–Marquardt algorithm, reduced to 1×10^{-5}, reflecting stable training behavior. Additionally, the validation checks reached a maximum of six, at which point training was stopped to prevent overfitting. These results confirm that the training process was efficient and well-regularized, ensuring a balance between accuracy and generalization capability.

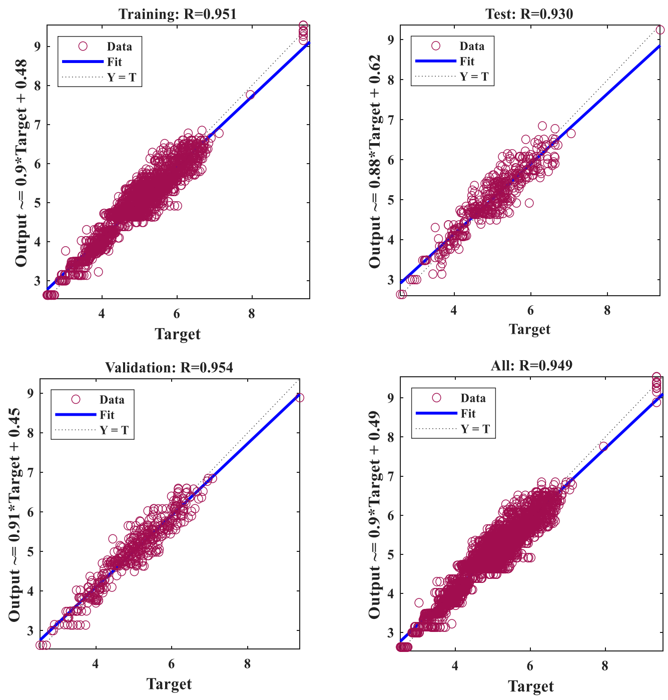


Fig. 4. Regression plots of the developed ANN model for overall training, testing, and validation datasets. The high R values demonstrate the strong agreement between predicted and actual values of SN

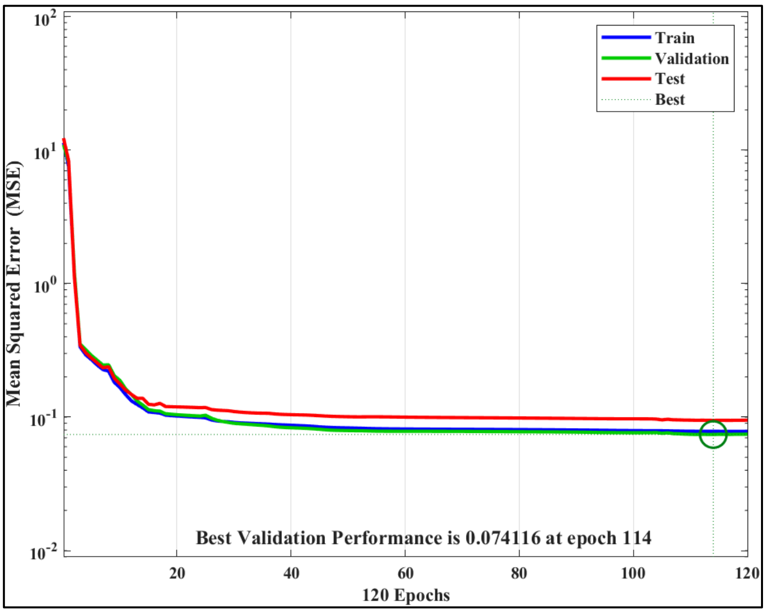


Fig. 5. Training performance of the ANN model showing mean squared error (MSE) variation with epochs for training, validation, and testing subsets. The best validation performance (MSE = 0.074116) was achieved at Epoch 114

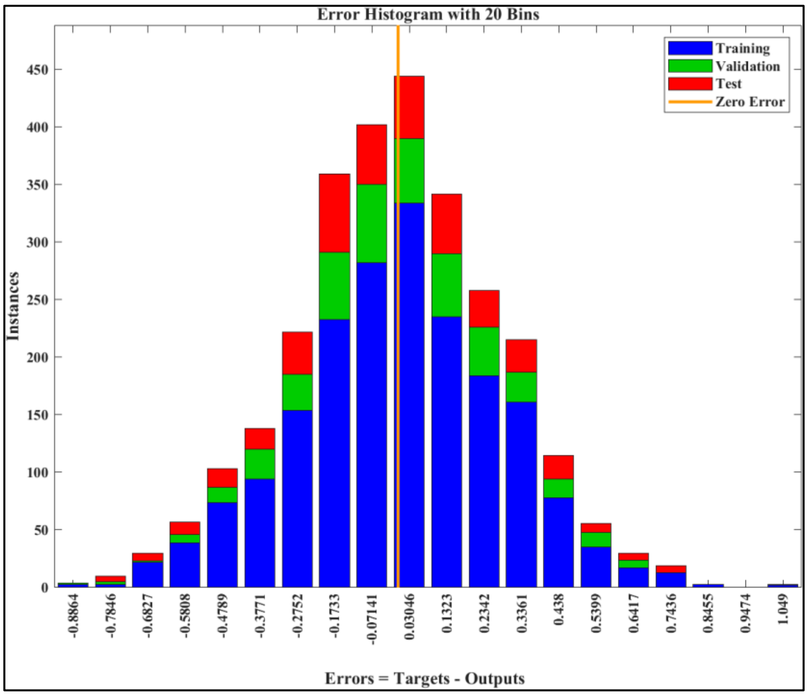


Fig. 6. Error histogram of the ANN predictions for training, validation, and testing subsets. Most residuals are concentrated around zero, confirming the accuracy and stability of the model.

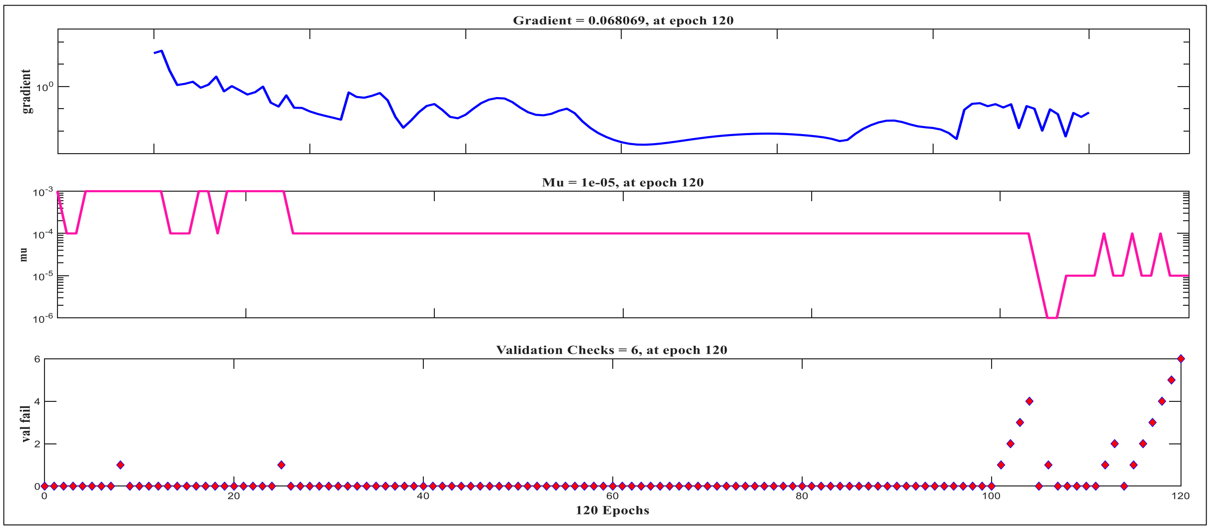


Fig. 7. Overall status of the ANN training process showing; top gradient, middle Mu, and bottom validation check over 120 epochs. The decreasing gradient, stable Mu, and limited validation checks indicate effective convergence and well-regularized training.

4. Conclusion

This study developed an artificial neural network (ANN) model to predict the structural number (SN) of flexible pavements using fundamental subgrade soil properties and environmental conditions. By utilizing moisture content (w), dry unit weight (γd), weighted plasticity index (wPI), and freeze–thaw cycles (NFT) as input variables, the model successfully replaced costly resilient modulus (MR) and CBR tests traditionally required in the AASHTO design procedure. The ANN, trained with the Levenberg–Marquardt algorithm and optimized with a single hidden layer of 10 neurons, demonstrated excellent performance, achieving R values above 0.930 across training, validation, and testing subsets.

The results indicate that the ANN successfully captured the nonlinear relationships between soil properties and pavement structural capacity. Convergence of the training and validation curves, along with error distributions centered around zero, confirmed that the model generalized well without overfitting. These findings are in agreement with the study by Ziar (2025), which evaluated four machine learning algorithms for predicting structural numbers and identified gradient boosting as the most effective model (Ziar, 2025). Both studies highlight that machine learning techniques can reliably predict pavement structural capacity using readily available subgrade properties and environmental factors, reducing reliance on time-consuming and expensive laboratory tests.

Overall, the results demonstrate that machine learning approaches, including ANN, offer practical, accurate, and cost-effective tools for flexible pavement design, supporting more efficient and informed decision-making in pavement engineering.

Looking ahead, future studies should broaden the current modeling framework by incorporating variable traffic levels. While this work relied on a fixed traffic load and predefined design parameters, in practice the cumulative number of equivalent single axle loads (ESALs) differs significantly across roadway classes. Integrating a wider spectrum of traffic conditions would improve the versatility and applicability of ANN-based predictions in diverse pavement design contexts.

In addition, because of the limited availability of base and subbase layer data, this study concentrated on the overall structural number, which is largely governed by subgrade behavior. Expanding the model to include layer-specific properties of base and subbase materials would allow for more refined predictions of each pavement component's contribution to SN. Such enhancements would pave the way for a more detailed, accurate, and optimized pavement design framework driven by machine learning.

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Exploring the Factors Influencing Individual Investor Behavior (A Conceptual Framework)

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Abstract:

This study presents a comprehensive review of the literature examining the diverse factors that shape individual investor behavior. The analysis is organized around five major dimensions demographic characteristics, psychological biases, experiential influences, informational aspects, and governance mechanisms. Drawing upon both traditional and behavioral finance theories, the paper explores how investors' decisions are driven not only by rational evaluation but also by cognitive limitations, emotional responses, and contextual environments. It highlights the complexity and heterogeneity of investor behavior, illustrating how deviations from classical rational models arise due to common biases such as overconfidence, loss aversion, and herding tendencies. By synthesizing insights across disciplines, the study develops a conceptual framework that integrates demographic and psychological attributes with institutional and informational dynamics. This framework enhances the understanding of how personal traits, learning experiences, and corporate governance structures interact to influence financial decision-making. The findings carry significant implications for policymakers, educators, and market regulators aiming to strengthen investor confidence, promote financial literacy, and ensure transparent reporting practices. In a rapidly evolving financial landscape characterized by digital trading and global connectivity, this review underscores the importance of understanding behavioral patterns to design policies and educational programs that foster rational, informed, and sustainable investment behavior.

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1. Introduction

Understanding the behavior of individual investors has emerged as a vital area of inquiry in the field of behavioral finance. Unlike institutional investors, individual investors often make decisions based on personal characteristics, emotions, and perceptions rather than purely rational analysis (Chang & Wei, 2011). The growing accessibility of financial markets and digital trading platforms has further increased the participation of individual investors, thereby amplifying the significance of their behavior in influencing market dynamics.

Prior studies have shown that psychological biases such as overconfidence, herding, and risk aversion play a central role in shaping investment decisions (Barberis & Thaler, 2003; Baker & Nofsinger, 2010). Additionally, demographic and experiential characteristics—such as age, gender, education, and investment experience—have been identified as key determinants of individual investment behavior (Barber & Odean, 2001; Baker et al., 2018; Heshmat, 2012). Moreover, access to information and the perceived credibility of sources significantly affect the confidence and strategies of retail investors (Heshmat, 2012; Lodhi, 2014). In the context of corporate governance, elements such as board competence and independence also influence investor perceptions and decision-making, particularly in emerging markets where institutional trust may vary (Sharma, 2006; Wagner, 2011).

This study proposes a conceptual framework that synthesizes five broad categories of factors influencing individual investor behavior: demographic, psychological, experiential, informational, and governance-related. By integrating theoretical and empirical insights across disciplines, this paper contributes to a more nuanced understanding of the multifaceted nature of individual investment behavior. Such a framework not only advances academic research but also informs financial educators, policymakers, and market regulators aiming to enhance investor protection, financial literacy, and market participation.

2. Methodology

This study employs a narrative, integrative literature review rather than a systematic review. Following the conventions of leading conceptual papers in accounting and behavioral finance, the selection of studies was driven by conceptual relevance rather than by rigid protocols. Seminal papers, influential empirical studies, and contemporary theoretical contributions were included to capture the broad intellectual foundations underlying demographic, psychological, experiential, informational, and governance-related determinants of individual investor behavior.

The literature was reviewed to synthesize ideas and identify recurring themes rather than exhaustively cataloging all publications on the topic. Consistent with prior conceptual reviews (e.g., Barberis & Thaler, 2003; DeFond & Zhang, 2014), the thematic structure emerged inductively as the literature was examined. Studies were organized according to the core dimensions of this paper, allowing the review to connect insights from behavioral finance, corporate governance, and decision-making research into a unified conceptual lens. The conceptual framework developed in this paper is the result of integrating these themes with established theoretical perspectives. Rather than using systematic coding or empirical testing, the framework reflects analytical reasoning and conceptual synthesis.

3. Theoretical Background

Individual investor behavior can be understood through several theoretical lenses, drawing from both traditional finance and behavioral finance. This section outlines key theories that serve as the foundation for exploring the factors influencing investment decisions made by individual investors. These theories include the rational decision-making models of traditional finance, the psychological insights of behavioral finance, and the role of governance structures.

3.1. Rational Choice Theory and Traditional Finance Models

Traditional finance models, grounded in Rational Choice Theory, assume that individuals make decisions by logically evaluating all available information and selecting the option that maximizes their utility (Scott, 2000). Modern Portfolio Theory (MPT), developed by Markowitz in 1952, asserts that investors seek to construct an efficient portfolio by optimizing the trade-off between risk and return (as cited in Fabozzi et al., 2002) under the assumption that they are rational and make decisions based on available information. The Efficient Market Hypothesis (EMH), proposed by Fama (1970), argues that asset prices reflect all available information, making it impossible for investors to consistently outperform the market. According to this view, market participants make optimal decisions, and any deviation from the rational model would be temporary and self-correcting. However, behavioral finance has increasingly challenged these models, particularly under conditions of uncertainty and incomplete information. Empirical observations show that investor behavior often deviates from rational expectations due to psychological biases, such as loss aversion and overconfidence (Kahneman & Tversky, 1979; Barberis & Thaler, 2003), which can lead to persistent anomalies that traditional models cannot fully explain.

3.2. Behavioral Finance and Psychological Biases

Behavioral finance emerged as a response to the limitations of traditional finance models, explaining market inefficiencies through the lens of human behavior (Barberis & Thaler, 2003). Initially resisted, it is now gaining mainstream acceptance (Baker & Nofsinger, 2010). A key assumption is that the structure of information and the traits of market participants significantly influence investment decisions and market outcomes unlike computers, the human brain relies on cognitive shortcuts and emotional biases, which lead to irrational decisions, violations of risk aversion, and systematic forecasting errors (Baker & Nofsinger, 2010). Prospect Theory (Kahneman & Tversky, 1979) is a cornerstone of behavioral finance, it suggests that investors evaluate potential gains and losses asymmetrically, with losses having a greater emotional impact than equivalent gains. This phenomenon, known as loss aversion, can lead to irrational behaviors, such as the disposition effect, where investors hold onto losing investments too long in the hope that they will recover or sell winning investments too early to lock in gains (Shefrin & Statman, 1985). Quispe-Torreblanca et al. (2025) provide novel evidence that mere attention can reshape investor reference points. They find that when investors log in to their brokerage accounts, the prices they observe become a new psychological benchmark for evaluating future gains and losses.

Consequently, investors tend to sell stocks that have appreciated since their last login, even if the change is small, because the recently viewed price anchors their perception of profit. This login-based disposition effect extends traditional prospect-theory explanations by showing that shifts in attention and information exposure continually reset reference points, influencing trading behavior and risk attitudes. Another important psychological bias is overconfidence. Overconfident investors tend to overestimate their abilities and knowledge, leading to excessive risk-taking, overtrading, and inadequate portfolio diversification (Barber & Odean, 2001). Similarly, heuristics (mental shortcuts) such as representativeness bias (judging probabilities based on stereotypes) (Tversky & Kahneman, 1974), and framing effects (the way information is presented) often lead investors to make decisions that deviate from rational models (Tversky & Kahneman, 1981). Mental Accounting is another concept in behavioral finance, in which individuals compartmentalize their financial decisions into separate accounts based on subjective criteria rather than considering their overall financial position; this behavior can lead to decisions that are not aligned with the investor’s long-term financial goals (Thaler, 1985).

3.3. Information Asymmetry and Financial Literacy

A key theory in understanding investor behavior is Information Asymmetry, which occurs when one party holds more or better information than the other in a transaction (Mishra et al., 1998). This imbalance can result in suboptimal decision-making in financial markets. When investors lack access to timely or accurate information, making well-informed choices becomes challenging. Akerlof (1970) illustrated this concept by showing that when buyers cannot distinguish between high- and low-quality assets, the market tends to be flooded with lower-quality options, thereby undermining overall market efficiency. Similarly, in financial markets, information gaps can lead to suboptimal investment decisions and asset mispricing, which eventually affect the investor's trust and, thereby, behavior. Financial literacy is key in mitigating information asymmetry and its effects on investment decisions. According to Heshmat (2012), female Saudi students with higher financial education were found to make more informed decisions regarding stock ownership, as they were better able to manage the psychological biases that often influence investment behavior.

3.4. Agency Theory and Governance

Corporate governance plays an essential role in shaping investor behavior, particularly in how investors perceive the risks and potential returns of an investment. Agency Theory (Jensen & Meckling, 1976) posits that there is an inherent conflict of interest between managers (agents) and shareholders (principals). This conflict arises because managers may prioritize their personal interests over those of shareholders, potentially leading to inefficiencies, risk-taking, or corporate misconduct.

In terms of how investors behave, a robust corporate governance framework is essential for sustaining investor trust (Dibra, 2016). This framework guarantees that choices are aligned with the interests of stakeholders and the long-term value of the firm (Guluma, 2021), which can influence investor decision-making. For example, investors may be more inclined to invest in companies with strong governance practices (Shleifer & Vishny, 1997). When investors are protected from expropriation, they are willing to pay more for securities, which further increases the appeal of these firms (La Porta et al., 1999).

4. Literature Review:

Several studies have identified a wide array of factors influencing individual investor behavior. These factors can be categorized into demographic, psychological, experiential, informational, and governance dimensions, all of which significantly shape investment decisions as illustrated in Figure 1.

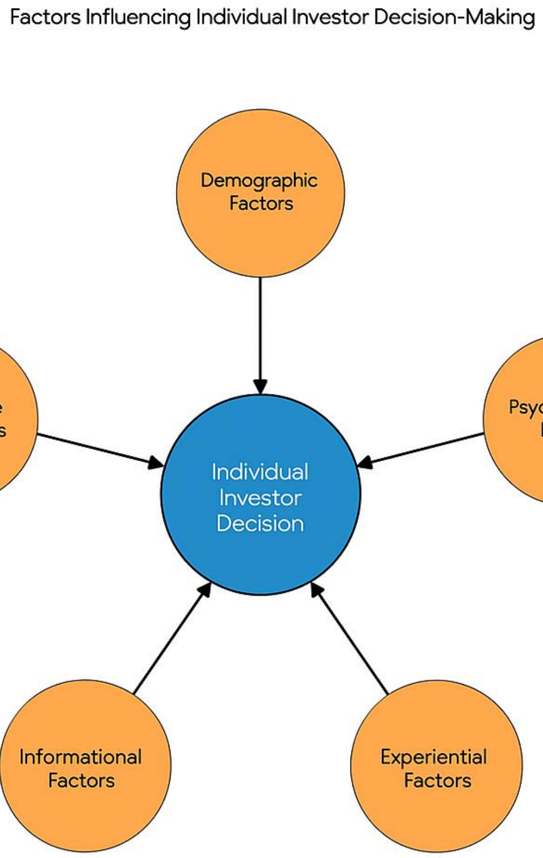

Fig. 1 Factors influencing individual investor behavior

4.1. Demographic Factors

Demographic variables such as age, gender, and education level have consistently been linked to investment choices. Age, for instance, influences risk preferences and portfolio diversification. Older investors tend to hold more diversified portfolios and achieve better risk-adjusted returns than younger or first-time investors (Baker et al., 2018). This aligns with findings from Lodhi (2014), who emphasized that older investors in emerging markets often prioritize stability and lower-risk investments. Gender also plays a crucial role. Women tend to be more cautious and risk-averse, leading them to trade less frequently than men (Barber & Odean, 2001). However, this difference has been found to decrease as financial literacy increases and women gain more experience in investing (Hsu et al., 2021). Education level is another critical demographic factor.

Higher education levels are often associated with greater financial literacy, leading to better-informed investment decisions (Heshmat, 2012). In particular, educated investors are more likely to diversify their portfolios and make decisions based on rational analysis rather than cognitive biases (Baker et al., 2018).

4.2. Psychological Factors

Prospect Theory (Kahneman & Tversky, 1979) offers a powerful lens for understanding how psychology shapes investment decisions. One of its central principles, loss aversion, explains that people feel the pain of losing money more intensely than the pleasure of gaining an equivalent amount. In investment contexts, this often leads individuals to hold on to losing stocks in the hope of recovery while selling winning ones too early to "lock in" profits (Odean, 1998; Shefrin & Statman, 1985). Another insight from Prospect Theory is the framing effect, which shows that the way information is presented can significantly alter decision outcomes. Tversky and Kahneman (1981) demonstrated that investors tend to be risk-averse when choices are framed as gains but risk-seeking when framed as potential losses. These findings highlight that emotions and perceptions, not just logic, strongly influence investment behavior.

Beyond Prospect Theory, several other psychological biases shape how investors think and act. One of the most prevalent is overconfidence, which leads investors to overestimate their knowledge and predictive abilities. This bias often results in excessive trading and insufficient portfolio diversification (Barber & Odean, 2001). Glaser and Weber (2007) further explain that overconfident investors underestimate risks and overvalue their potential returns, ultimately undermining performance. More recently, Musnadi et al. (2025) found that overconfidence mediates the relationship between information processing and trading aggressiveness, suggesting that psychological self-assurance influences how investors interpret and respond to financial signals. In other words, the more confident investors feel, the more likely they are to act boldly even when their information is incomplete.

Recent research has expanded the understanding of these behavioral tendencies by examining the physiological dimensions of investor psychology. Quang et al. (2025) introduced a physiological–behavioral perspective, showing that factors such as sleep quality influence trading intensity and risk exposure. Their findings suggest that cognitive resources—such as alertness, attention, and fatigue play an important role in determining how susceptible investors are to behavioral biases. Inadequate rest can impair self-control and judgment, making investors more likely to engage in impulsive, emotionally driven decisions. This connection between mental and physical states highlights that decision-making quality is not only a function of information and cognition but also of the investor's overall physiological condition.

Other biases such as anchoring, availability bias, regret aversion, mental accounting, and representativeness—further illustrate how people rely on cognitive shortcuts when making investment decisions. Chandra and Kumar (2012) found that these heuristics often exert stronger influence than rational analysis, showing that investors rely on a mix of emotional and intuitive reasoning. Emotions themselves can magnify these effects. Baker and Ricciardi (2014) note that feelings such as fear, excitement, or regret can heighten cognitive biases, pushing investors toward impulsive or irrational decisions. Taken together, these studies affirm that investment behavior is rarely purely rational. Instead, it emerges from a dynamic interplay of cognition, emotion, and even physiological state—all of which shape how individuals perceive, interpret, and react to financial uncertainty.

4.3. Experiential Factors

Experience plays a crucial role in shaping how investors approach the market. Experienced investors tend to exhibit fewer behavioral biases, such as overtrading or poor diversification, compared to novices. Koestner et al. (2017) found that experience helps investors avoid common mistakes, leading to improved returns over time. This is supported by Nicolosi et al. (2009), who found that experienced investors improve their trading decisions over time, adjusting their strategies based on their prior experience and stock selection skills. Learning, both from personal experience and from observing others, is another important aspect. Shantha et al. (2018) proposed that investors update their decision-making heuristics based on both reflective experience and social learning from peers. This social learning is especially important in today's digital environment, where investors frequently exchange tips and information through social media and online trading platforms. Furthermore, experience impacts how investors use environmental and financial information to make allocation decisions. Holm and Rikhardsson (2008) demonstrated that experienced investors are more effective at integrating complex information, which helps them make more informed decisions.

4.4. Informational Factors

Access to reliable and high-quality information is essential for making sound investment decisions. Among the most critical components of this process is financial literacy, which enables investors to evaluate opportunities objectively and make informed judgments. Heshmat (2012) found that individuals with stronger financial literacy are more capable of making rational choices and are less prone to behavioral biases such as overconfidence and loss aversion. The type and quality of information available also play an important role in shaping how investors behave. Financial reports, accounting data, and media coverage influence how investors perceive market trends and assess company performance. Lodhi (2014) demonstrated that investors with a stronger grasp of accounting and financial concepts are better equipped to reduce information asymmetry, which directly affects their willingness to take risks.

Building on this, Suroso and Istianingsih (2025) showed that perceived usefulness, ease of use, and consumer knowledge jointly shape investment behavior, suggesting that technological familiarity increasingly determines how investors access and trust financial information. Similarly, Chandra and Kumar (2012) observed that when faced with information asymmetry, investors tend to rely on simple, easily accessible cues due to the cognitive effort required to process complex financial data. This tendency can influence both their risk preferences and their susceptibility to behavioral biases.

In today's digital environment, the volume and speed of information dissemination have grown dramatically. Riefel (2024) found that social media platforms amplify market volatility by spreading peer opinions and market signals almost instantaneously, often prompting emotionally driven and short-term reactions. Consistent with this, Awad et al. (2025) provided strong evidence that real-time digital interactions heighten herding tendencies and overconfidence, leading to excessive trading and speculative behavior. Together, these studies demonstrate that the availability, accessibility, and interpretation of information are central to investor decision-making, where literacy, technology, and emotion interact to shape how individuals navigate modern financial markets.

4.5. Governance Factors

Corporate governance structures are another critical domain influencing investor behavior. Several studies have highlighted that individual investors' perceptions and, by extension, their investment decisions, are strongly influenced by various aspects of corporate governance (e.g, 2006; Cheung et al., 2007; Almer et al., 2008; Chang & Wei, 2011; Sharma; Park & Oh, 2022; Alduais et al., 2023). Almer et al. (2008) found that non-professional investors' judgments of credibility are particularly impacted by governance-related actions, including changes in the board composition, audit processes, and executive leadership. Similarly, Chang and Wei (2011) observed a positive relationship between effective governance practices and individual investor preferences, suggesting that investors are more inclined to favor companies with strong governance frameworks. Alduais et al. (2023) underscored the importance of well-established governance structures in enhancing investor confidence, which is essential for attracting and retaining investments, especially in emerging markets. Park and Oh (2022) noted the growing importance of Environmental, Social, and Governance (ESG) factors among individual investors, demonstrating the increasing relevance of governance in their personal investment decisions. Furthermore, Sharma (2006) highlighted that both professional and non-professional investors are significantly influenced by their perceptions of board effectiveness, emphasizing the critical role the board plays in ensuring governance credibility. Finally, Cheung et al. (2007) found that investors tend to place higher value on assets associated with firms that exhibit stronger corporate governance practices.

5. Conclusion

This study has developed a comprehensive conceptual framework that synthesizes a wide spectrum of factors influencing individual investor behavior, categorized into five principal domains: demographic characteristics, psychological biases, experience levels, informational dynamics, and governance structures. By integrating insights from both traditional finance and behavioral finance theories this framework offers a multi-theoretical lens through which investor decision-making can be more holistically understood.

The findings emphasize that individual investors do not always conform to the rational actor model assumed in classical finance. Instead, their decisions are frequently shaped by cognitive limitations, emotional biases, and contextual influences, including the quality of information and the integrity of corporate governance structures. In today's increasingly democratized and digitized financial markets, understanding these behavioral dynamics is critical for a range of stakeholders. For policymakers and regulators, the framework provides guidance on how investor protection and market stability can be enhanced by promoting financial literacy, reducing information asymmetries, and enforcing robust governance practices. For practitioners and financial advisors, it underscores the need for personalized investment strategies that align with individual behavioral tendencies and constraints.

Finally, for the academic community, the framework lays the groundwork for future empirical research that can test the interrelations among these factors in diverse cultural and market contexts.

Ultimately, this study contributes to the growing body of literature that seeks to humanize the finance discipline by recognizing that investor behavior is not merely a function of economic rationality, but a complex interplay of psychological, social, informational, and institutional forces. A deeper appreciation of this complexity can foster more inclusive financial systems, support better investment outcomes, and inform the development of policies that enhance the overall functioning of capital markets.

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