Developing an Enterprise Risk Management Model through Meta-Analysis and Comparing its Predictive Power with the Hoyt and Liebenberg Model (2011)

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Abstract: This study was conducted with the aim of developing an enterprise risk management (ERM) model using a meta-analysis approach and comparing its predictive power with the Hoyt and Liebenberg (2011) model. To achieve this, employing the meta-analysis technique, all Persian-language articles published between 2011 and 2025 were examined. The research is developmental and applied in nature, and an inferential approach was used to interpret the results. The findings of the study were presented in several parts. The first part sought to identify the degree of accuracy of the Hoyt and Liebenberg (2011) model in predicting enterprise risk management. In this section, the results of using the neural network method showed that the mean squared error (MSE) was equal to 0.00080. In the second step, for the development of the enterprise risk management model, a systematic review of the literature demonstrated that a set of quantitative and qualitative variables significantly influence the maturity and effectiveness of risk management processes. These variables include operational growth opportunities, the market-to-book value ratio of equity, the risk-free interest rate, operational efficiency, stock market growth, tax orientations, corporate governance-related indices, corporate social responsibility, the firm's information environment, CEO efficiency, CEO personality traits, board of directors' characteristics, audit attributes, and the life cycle. These factors were added to the initial model. In addition, when comparing the predictive power of the developed model with the base model, the results indicated that the base model, after training, achieved an MSE of approximately 0.00080 and an RMSE of ≈0.0283. However, the developed model succeeded in reducing the MSE to 0.000422 and the RMSE to 0.020548. This substantial reduction (over 47% in MSE and more than 27% in RMSE compared to the base model) confirms that adding institutional and operational components enhanced the model's ability to more accurately reproduce the ERMI index. This indicates that the developed model not only has a lower average error but also improves error stability and significantly reduces the probability of severe errors. Overall, comparing these two structures demonstrates that incorporating new variables from the literature and institutional and financial functions, in addition to emphasizing the core aspects of the base model, significantly improves predictive performance. Based on the findings of this research, it can be concluded that the efforts made in this study resulted in the development of a localized model with superior predictive power compared to conventional enterprise risk management models.

Keywords: Enterprise risk management, Hoyt and Liebenberg (2011) enterprise risk management model

1. Introduction

Enterprise Risk Management (ERM) has evolved from a compliance-oriented checklist into a strategic, analytics-enabled capability that integrates risk appetite, capital allocation, and performance management across the enterprise. In capital-intensive and data-rich sectors—banking, insurance, and digital supply chains—boards and executives increasingly view ERM as an enabler of resilience, not merely a cost center, particularly as organizations absorb lessons from systemic shocks and technology-driven disruptions [1, 2]. At the same time, emerging evidence from developing and transition economies shows that ERM design and intensity are strongly conditioned by institutional quality, information environments, and governance practices, requiring models that are sensitive to context and firm heterogeneity [3-5]. Against this backdrop, the present study develops an extended, data-driven ERM measurement and prediction framework and contrasts its predictive power with a baseline specification widely cited in the ERM literature, while grounding the model in governance, disclosure, and market microstructure insights documented in recent research [6-8].

Several converging streams motivate the need for an enriched ERM modeling approach. First, post-pandemic scholarship highlights how tail dependencies and contagion dynamics transform localized shocks into enterprise-level and sector-wide crises, thereby exposing limitations of narrowly financial risk metrics [2, 9]. Disruptions to logistics and input markets have reinforced the value of network-aware ERM, scenario analysis, and early-warning indicators that combine operational telemetry with external risk signals, including epidemiological or cyber-threat propagation parameters [2, 10]. Second, the digitalization of financial intermediation and the spread of learning algorithms in front-, middle-, and back-office functions have lowered the cost of predictive analytics for risk identification and stress testing, accelerating the diffusion of ERM practices into small and medium-sized enterprises (SMEs) and public service organizations [3, 11]. Third, research in emerging markets shows that board structures, internal controls, and risk disclosure quality are not add-ons but intrinsic levers that shape firms' systematic and idiosyncratic risk through incentive design and information quality effects [5, 8, 12]. These developments imply that ERM measurement must integrate financial, operational, and institutional features to capture how organizations truly bear, transfer, and transform risk.

Within corporate governance, board composition and leadership characteristics have been linked to risk outcomes both directly and via mediating channels such as disclosure policies and managerial myopia. Evidence from listed firms indicates that gender diversity on boards can dampen exposure to systematic risk when complemented by CEO governance that avoids excessive power concentration; these relationships operate through monitoring quality and information flow to capital markets [12]. CEO attributes, including power dynamics and behavioral tendencies, have also been associated with tail-risk realizations in equity markets, underscoring the role of executive decision styles in risk escalation and crash vulnerability [13]. Complementarily, the structure and expertise of audit committees condition risk disclosure and, by extension, investors' ability to price risk, suggesting that ERM proxies built solely from financial ratios risk omitting critical governance signals [8]. In tandem, corporate social responsibility (CSR) policies influence real earnings management motives and the alignment (or misalignment) between risk posture and stakeholder expectations—an alignment that can stabilize funding conditions and reduce risk premia when credible [7].

Market-based and macro-fiscal channels form a second pillar of ERM design. Empirical studies show that the market-to-book equity ratio embeds investor expectations about growth, profitability durability, and risk, while systematic risk on local exchanges is shaped by firm fundamentals and factor exposures that interact with liquidity regimes [14]. At the policy interface, tax uncertainty and enforcement intensity transmit into firms' cash-flow volatility and compliance risk, which in turn affect investment timing and leverage decisions—features that a comprehensive ERM index should heed if it is to predict risk realization rather than merely describe past volatility [15]. In banking, asset-liability management (ALM) frameworks rooted in feedback-rich system dynamics highlight how balance-sheet decisions coevolve with interest-rate and liquidity risks; such models emphasize endogenous risk amplification and the need to integrate structural and policy variables into ERM [16]. These insights collectively argue for ERM modeling that engages with fiscal, monetary, and market microstructure determinants of firm-level risk.

A third pillar centers on operations, cyber-physical systems, and supply chain resilience. As cloud platforms and Industry 4.0 architectures diffuse, exposure shifts from purely financial shocks toward intertwined cyber and operational risks. Cross-sectional evidence from manufacturing and logistics confirms that information-system security practices and cyber supply-chain risk management correlate with performance and survivability under stress, implying that ERM indicators should incorporate security governance and incident-response maturity [10]. Epidemic-style models of disruption propagation further show how local failures cascade through supplier networks, elevating the value of early-containment strategies and buffer capacity—considerations that standard financial ERM ratios do not capture [2]. These operational channels intersect with marketing and service ecosystems as well; risk management capabilities align with sustainable marketing orientations and customer trust maintenance, particularly in service industries such as fitness and tourism where reputational spillovers are acute [17].

The adoption and depth of ERM vary meaningfully by firm size, ownership, and external finance conditions. In Malaysian SMEs, ERM uptake is shaped by cost-benefit perceptions, managerial cognition, and institutional supports, pointing to path dependence and resource constraints in capability building [3]. Evidence from Czech SMEs indicates that foreign capital participation tends to strengthen ERM implementation, potentially via governance transplants and technology transfer; this improved practice may then translate—directly or indirectly—into superior financial performance [18, 19]. In African banking systems, the linkage between ERM and performance sustainability underscores risk culture and regulatory architecture as key moderators, highlighting that the same ERM "inputs" can yield different performance "outputs" under divergent institutional environments [4]. Insurers' risk-taking in South Africa similarly depends on corporate governance quality and ERM sophistication, with threshold behavior suggesting nonlinear payoffs to governance improvements [20]. These findings motivate models that are attentive to firm-life-cycle stages, capital structure, and institutional embedding.

Within Iran's market context, studies document the practical challenges of ERM implementation and the benefits of systematic identification, analysis, and evaluation processes in financial institutions, yet also underscore heterogeneity in information quality and governance that complicates cross-firm comparisons [5, 21]. Research on knowledge-based risk management models in ICT companies further suggests that organizational learning and knowledge flows can be deliberately harnessed to strengthen risk identification and response, especially where tacit operational knowledge is a key asset [22]. At the strategic level, ERM has been linked to competitive advantage and performance via financial literacy and capability channels; capability scaffolds appear to mediate how ERM translates into measurable value creation, a mechanism our modeling approach seeks to capture via governance and information variables [23]. Complementary work stresses the need to articulate risk management across organizational layers with clear strategy maps, ensuring that portfolio choices and project governance reflect enterprise risk appetite rather than siloed metrics [24, 25].

Methodologically, modern ERM benefits from advances in simulation, stochastic design, and learning-based prediction. Multi-agent models can encode strategic interaction among market participants, regulators, and firms, enabling exploration of dynamic risk equilibria under varying decision rules—a perspective increasingly used in stock-market prediction and risk management tasks [26, 27]. On the estimation side, quasi-random sequence methods can improve exploration of high-dimensional parameter spaces and, in some applications, outperform conventional Markov Chain Monte Carlo (MCMC) sampling in convergence speed and coverage—advantages that matter when integrating many operational and governance covariates into ERM [28]. For feature discovery and early-warning signals, predictive analytics pipelines from finance demonstrate how machine learning augments traditional econometrics for scenario discrimination and stress classification, provided that models remain interpretable and auditable for governance purposes [11]. In manufacturing SMEs, fuzzy multi-criteria decision frameworks have been used to prioritize dynamic ERM success factors, bridging qualitative managerial judgments with quantitative scoring in environments of ambiguity [6]. These methodological trends converge on a practical imperative: use data-efficient learners and simulation engines to integrate financial, operational, and institutional drivers in ERM.

Our study responds to these theoretical and practical currents by assembling a feature set that extends standard financial determinants—firm size, leverage, profitability, growth, and payout policy—with institutional and operational variables documented in recent literature. We incorporate board and audit committee characteristics, internal control strength, managerial structure, CSR posture, and the information environment as proximate determinants of disclosure quality and risk culture [5, 7, 8]. We also integrate market-based controls (market-to-book as an expectations proxy), fiscal risk (tax revenue volatility and tax policy risk), and macro-financial channels (risk-free rate) that map policy shocks and investor sentiment into firm-level exposure [14, 15]. Life-cycle stage is included to capture maturation effects in risk management capabilities and systematic risk profiles documented on the Tehran Stock Exchange [29]. Importantly, we reflect operational efficiency and stock-market growth as conduits between process stability, liquidity conditions, and enterprise risk posture, in line with evidence on how operations and market regimes interact to shape realized risk [30, 31]. Within service and consumer-facing sectors, we recognize that risk governance co-determines marketing orientation and stakeholder trust architectures, further reinforcing the enterprise-wide nature of risk management [17]. Finally, we situate our modeling within the broader systems context of banking ALM and dynamic feedbacks, consistent with system-dynamics approaches to balance-sheet risk [16].

From a policy and managerial perspective, cross-country comparisons reinforce that ERM is not a one-size-fits-all artifact. Adoption drivers in Malaysian SMEs differ from those in Czech or African contexts, where foreign ownership and regulatory intensity, respectively, condition ERM depth and its performance linkages [3, 4, 18-20]. Within Iran, empirical case work shows that practical implementation hinges on building integrated risk registers and aligning ERM workflows with governance committees and disclosure calendars, with documented performance benefits where information-quality management criteria are formalized and audited [5, 21]. Knowledge-centric models complement these structures by embedding organizational learning into risk identification and response, a design well suited to ICT and data-intensive firms [22]. Collectively, these insights justify our inclusion of governance, disclosure, life-cycle, and market-policy features in an ERM prediction architecture calibrated to a local market but resonant with international evidence [2, 6, 10].

In sum, the current article advances the ERM literature by (i) proposing an extended, context-aware ERM index function that integrates financial, operational, governance, and policy-proximate variables documented across multiple streams; (ii) employing contemporary predictive tools and simulation-informed insights to compare the extended specification with a widely used baseline; and (iii) situating the analysis within an emerging-market setting where information frictions and governance heterogeneity are first-order. By drawing on studies that span system dynamics in banking, cyber-operational risks in supply networks, knowledge-based risk processes in ICT firms, SME adoption pathways, and governance-driven disclosure quality, the study aims to demonstrate that ERM measurement and prediction materially improve when institutional and operational levers are explicitly modeled alongside financial fundamentals

2. Methodology

The present study is applied in terms of purpose and falls within the category of developmental research. Moreover, the meta-analysis method was employed for the development of the model. To this end, by reviewing prior research literature based on studies conducted in Iran that have investigated factors influencing enterprise risk management, variables that were not included in the initial model but whose effects on enterprise risk management were confirmed in previous studies were identified. After selecting the relevant articles, the reference lists of these studies were examined to identify additional relevant research.

To locate the required studies, electronic resources were reviewed first, followed by other techniques such as manual searches in journals or sending emails to authors and researchers. Scholars who utilize meta-analysis are expected to perform a comprehensive search to identify all eligible studies. In this research, the focus was on studies conducted in Iran that examined factors affecting enterprise risk management. Therefore, all scientific articles published in domestic databases such as Irandoc, Magiran, Noormags, and the Scientific Information Database (SID) of Jihad Daneshgahi were reviewed based on keywords including “risk,” “risk management,” and “enterprise risk.” Additionally, for comparing the proposed model with the Hoyt and Liebenberg (2011) model, the neural network method was applied.

To achieve the first objective, the statistical population of this research consisted of all studies conducted in Iran that examined factors affecting enterprise risk management. The characteristics of the articles included the following:

- The researchers examined investment efficiency.
- The research method was quantitative.
- Investment efficiency was considered as the dependent variable.
- The study was published in a journal indexed in ISC or classified as a scientific-research article.

3. Findings and Results

Given the predetermined objectives of the study, the present research was conducted in several stages.

Stage One: Determining the Predictive Power of the Hoyt and Liebenberg Model (2011)

In this stage, the base model (Hoyt and Liebenberg, 2011) was first described. The Hoyt and Liebenberg (2011) model is expressed as Equation (1).

Equation (1):

$$ERMI_i = f(Size_i \cdot Leverage_i \cdot ROA_i \cdot Salesgrowth_i \cdot Div\_Ind_i)$$

Accordingly, enterprise risk management is a function of firm size, financial leverage, sales growth, profitability, and dividend payout, with their operational measurement described as follows.

Firm Size (SIZE): Measured through the natural logarithm of total assets.

Financial Leverage (LEV): Measured using the ratio of total debt to total assets (Bayardo et al., 2022).

Return on Assets (ROA): Calculated by dividing net income by the total book value of assets at the end of the fiscal year.

Sales Growth (Sale.Gro): Calculated as the growth rate of net sales compared to the previous fiscal year.

Dividend Ratio (DIV): Defined as the ratio of earnings per share (EPS) to share price.

Data Extraction

In this stage, data were extracted based on the Hoyt and Liebenberg (2011) model. Information from 102 listed companies with complete data availability was evaluated and used as the foundation for analysis. To ensure consistent measurement across variables, normalization was applied to the data. This process enabled the preparation of panel data consisting of 816 rows for further analysis.

Training and Testing Data

In the data preprocessing stage, to ensure fair and accurate evaluation of the perceptron model's performance, the normalized dataset was divided into two separate subsets: 80% for training and 20% for final testing. The "Random Split" method ensured that both training and testing samples were randomly selected from the dataset, preventing bias from specific observation distributions. This random split allowed the model to learn from a diverse set of samples while ensuring that testing involved "unseen" data not included in training.

Design of the Perceptron Model

In this study, to implement the predictive model of the ERMI index, a simple neural network or perceptron was used, consisting only of one input layer and one output layer. The output layer comprised a single neuron with a linear activation function. This means the model's output is a linear combination of the inputs (research features). This minimal structure replicates the linear regression equation presented in the Hoyt and Liebenberg (2011) model, but in the neural network framework, it allows for automatic coefficient optimization and improved evaluation of the training process. Choosing a single-neuron perceptron with a linear activation function ensured both implementation simplicity and interpretability, while aligning the predictive behavior with the assumptions of classical linear regression. In this setup, the network weights directly correspond to regression coefficients, and the bias corresponds to the intercept of the Hoyt and Liebenberg model. Consequently, results from the network training could be directly compared with linear regression outputs, while benefiting from neural network features such as gradient-based optimization and optimized data partitioning.

Model Training

The model was trained on the training dataset for 100 epochs, with a batch size of 16. In each epoch, 20% of the training data was internally reserved for validation to monitor the learning process and detect potential overfitting.

Calculation and Interpretation of RMSE

To facilitate interpretation of model evaluation results, after calculating the mean squared error (MSE), the next step involved computing its square root, the root mean squared error (RMSE). Since MSE represents the mean of squared differences between actual and predicted values, its unit is squared, making direct interpretation difficult. By calculating $RMSE = \sqrt{MSE}$, the error returns to the same scale as the dependent variable (normalized ERMI), allowing for easier interpretation of the model's average deviation from actual values. In the final test on the test dataset, the perceptron model achieved an MSE of 0.00080. Calculating RMSE yielded a value of 0.0283 ($\sqrt{0.00080} = 0.0283$). Given that ERMI values were normalized within the range [0,1], this means the model's predictions had an average error of only 0.028 units, clearly indicating high accuracy of the perceptron in reproducing organizational risk levels.

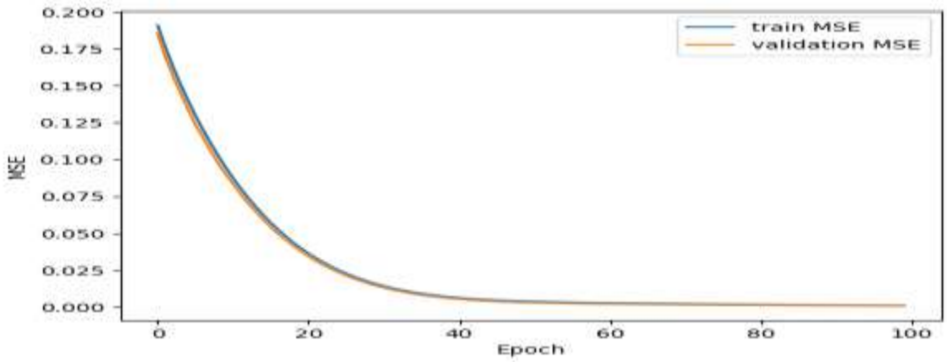


Figure 1. MSE Chart During Training Epochs

The chart demonstrated that at the start of training (early epochs), the MSE for both training and validation sets was approximately 0.18. However, within the first 20 epochs, the model error dropped steeply and consistently from 0.18 to around 0.02. From epochs 20 to 60, the error gradually decreased below 0.005, and by epochs 60–100, it approached nearly zero. This pattern indicated rapid initial learning by the perceptron model, followed by fine-tuning of coefficients to reach minimum error. Moreover, the training (blue line) and validation (orange line) MSE curves were nearly overlapping and parallel, with no significant divergence, suggesting the model not only learned the training data well but also generalized effectively without overfitting. Thus, the perceptron model with this configuration and normalized data provided stable and reliable generalization.

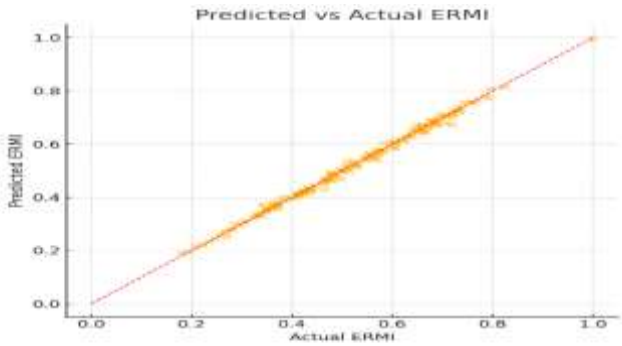


Figure 2. Scatter Plot of Predicted vs. Actual ERMI Values

In this scatter plot, the horizontal axis represented actual ERMI values, while the vertical axis showed predicted values. Orange points indicated individual test observations, and the red dashed line represented the 45-degree line (Actual = Predicted). The clustering of most points along this line highlighted the model's high predictive accuracy, while the small dispersion around the line confirmed minimal, non-systematic errors. Since data were normalized in the range [0,1], most points fell between 0.2 and 0.8, and the model predicted this range with little deviation. Only a few points deviated significantly from the line, reflecting outlier errors, but their impact on overall performance was negligible. Overall, the scatter plot confirmed the perceptron's strong performance in reproducing ERMI.

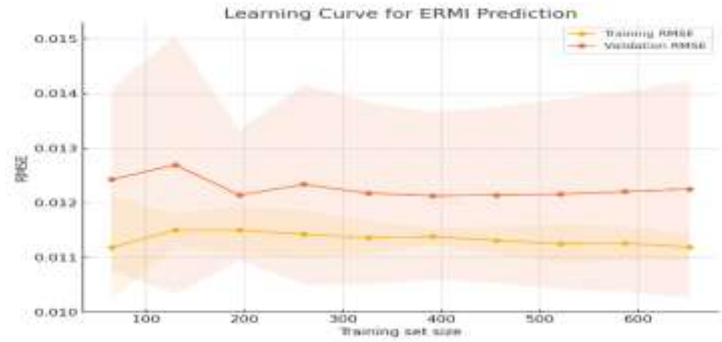


Figure 3. Learning Curve of the Model

The learning curve showed that as the proportion of training data increased from 10% to 100%, the RMSE of the model decreased for both training (yellow line) and validation (orange line) datasets, though the decline became more gradual. Specifically, the training RMSE slightly decreased from about 0.0112 at smaller sample sizes to approximately 0.0112 at larger sizes, while validation RMSE declined from about 0.0124 to 0.0122. This pattern indicated that adding more data contributed to model improvement up to a point, but beyond approximately 60% of data, further RMSE reduction was marginal, with the curves flattening.

The shaded area around the curves represented the standard deviation of RMSE across cross-validation folds. The wider band around the validation curve compared to training reflected slightly higher variability across validation folds, though overall fluctuations were small. The convergence of training and validation curves with relatively close values suggested no overfitting and stable performance. Thus, based on this curve, the existing dataset appeared sufficient for training the model, and adding more data beyond the current point would have limited impact on reducing prediction error.

Overall, this stage sought to evaluate the accuracy of the base model in predicting enterprise risk management. The results of the neural network approach indicated that MSE equaled 0.00080.

Stage Two: Proposing a Complementary Model for Enterprise Risk Management Using Meta-Analysis

To formulate the research question, the first step for researchers was to determine the specific focus of study. In the present research, the central question investigated was: “What are the new variables that can enhance the accuracy of measuring enterprise risk management?” This was formulated by considering the parameters listed in Table 1.

Table 1. Research Question

Parameters	Research Question Formulation
What (subject of study):	What categories and components influence enterprise risk management?
Who (study population):	Several databases and different search engines were examined in this research.
When (time limitation):	No time limitation was initially imposed for selecting relevant articles. However, after the database search, it was found that most useful and relevant articles (based on applied filters) were published from 2011 onward. Nevertheless, the final selection of articles was solely based on the needs and objectives of the research, without any strict temporal restriction.
How (method of obtaining studies):	This research applied the “documentary analysis” method, focusing on the analysis of secondary data.

Identification and Retrieval of Studies

In this research, domestic databases such as MAGIRAN, CIVILICA, SID, and others were searched to identify and collect various studies. In this process, whenever any of the relevant keywords appeared in the titles, abstracts, or main texts of the targeted studies, the article was initially selected as a preliminary input. In the second step, a combined search using the *OR* operator between keywords was applied. In addition, these approaches were combined together for broader coverage. An important point in this stage was that after reviewing the articles, by examining the reference lists of the initial studies, new articles were identified in other databases, which were also used for the final evaluation of the model. As a result, a total of 189 initial articles were identified and entered into the selection process.

Determining the Inclusion and Exclusion Criteria of Studies

In this stage, after identifying the preliminary articles, the process of selecting those relevant to the research needs was conducted through analysis of the core sections of each study. The selection and exclusion process is presented in Table 2.

Table 2. Inclusion and Exclusion Criteria of Articles

Stage	Selection Criteria	Number Selected	Number Excluded
Search based on keyword combinations using *AND–OR*	Presence of keywords in the title and search results	189	0
Removal of duplicates in documents	Duplicate title or article in multiple searches	50	139
Removal based on abstract and title review	Focus of study on the variables under investigation and relevance to research objectives	68	71
Removal based on title and general study content	Focus of study on the variables under investigation and relevance to research objectives	38	33
Removal after full-text review focusing on implementation indicators and feasibility	Relevance and usability of article text in the intended analysis	12	21
Final approved articles for analysis	21	—	

Extraction of Findings and Quality Assessment of Each Study

In this research, a checklist containing various criteria was used to assess the quality of each primary study as high, medium, or low. The purpose of scoring each study was to increase the validity of the research by using a proper checklist tool and to exclude low-quality studies from the synthesis process. Table 3 presents a sample of the checklist used to evaluate 8 studies based on the selected criteria.

Table 3. Sample Checklist for the Evaluation of 8 Studies

Row	Criterion	Study 1	Study 2	Study 3	Study 4	Study 5	Study 6	Study 7	Study 8
1	Clarity of research objectives	3	4	1	5	3	1	4	4
2	Logic of methodology	2	3	1	5	2	1	3	5
3	Research design	1	2	1	5	3	1	4	5
4	Sampling	3	4	2	4	4	2	4	5
5	Data collection	3	3	3	2	3	1	3	5
6	Reflexivity	4	3	4	5	4	2	3	4
7	Ethical considerations	3	3	1	4	3	1	4	5
8	Accuracy of analysis	4	3	1	5	2	1	4	4
9	Clarity of findings	3	2	2	5	4	2	3	5
10	Research value	3	1	2	5	3	1	1	4

Quality Level	—	Medium	Medium	Low	High	Medium	Weak	Medium	High
Remarks	—	Requires second reviewer's judgment	Requires second reviewer's judgment	—	Requires second reviewer's judgment	Requires second reviewer's judgment	Requires second reviewer's judgment	—	

At this stage, the extracted sources were independently reviewed by a second researcher (the "reviewer") based on the criteria listed in Table 4-4. In cases of rejection, the corresponding reason was recorded. If disagreement arose between the two reviewers, a "third reviewer" was assigned to adjudicate.

The "agreement rate" between the two reviewers was determined using the Kappa test. The Kappa index, known as Cohen's Kappa, ranges from 0 to 1. In this study, the Kappa value was 0.72, indicating a high level of agreement between the two reviewers. Finally, all "included studies" were checked and approved by a subject matter expert in the field. The sources were provided to the reviewers in a blinded format, with the author's name, institution, and journal information removed.

Open Coding and Tabulation of Data

In this section, after synthesizing the articles and categorizing them, the results and texts of the papers were examined. Based on the main objectives—namely, identifying the components and subcomponents related to the feasibility and implementation model of smart underwriting—sentences containing relevant semantic phrases were extracted, and for each semantic phrase, an associated open code was designated. These open codes were grouped into various categories under the label of core factors.

In line with extending the baseline enterprise risk management model and increasing the predictive accuracy of the ERMI index, the first step—a systematic review of the literature—showed that a set of quantitative and qualitative variables has a substantial impact on the maturity and effectiveness of risk-management processes. First, operational growth opportunities, denoted as GRAWOP and introduced by [30], were considered as a measure of a firm's internal development capacity; this variable indicates the extent to which a firm, when facing potential risks, can exploit new markets or expand product lines. Second, the market-to-book equity ratio (MKTBK), derived from the studies of Saeedi et al. (2011) and [14], was incorporated into the model formula as an indicator of investors' expectations and the informational quality of the market, because investors price a firm's risk-taking by assessing its performance trajectory [14, 32]. The risk-free interest rate (INTRATE), highlighted by Saeedi et al. (2011), is another variable added to adjust expected returns under different economic conditions; this rate reflects how the opportunity cost of investing in the firm aligns with the country's monetary environment [32]. Furthermore, the effect of operational efficiency (OPEFFE) on the model was established based on the results of Moqarrab et al. (2021) and Qanbili et al. (2018), as optimized production and service processes can reduce performance volatility and provide greater stability to the risk-management framework [25, 33]. Stock market growth (GSM), extracted from Hemmatfar and Saqefi (2014) and [14], reflects the gap between expectations and political-economic realities in risk-taking decisions and indicates the degree of mobility and liquidity of a firm's shares [14, 34].

Tax orientations, captured as volatility in tax revenues (TAX/REV) and tax risk (TAXRISK), were incorporated from the works of Hemmatfar and Saqefi (2014), [31], Ghorbani et al. (2014), and [15], because delays in tax payments or exposure to changes in tax policy can intensify liquidity risk and regulatory non-compliance [15, 31, 34, 35]. In the domain of corporate governance and institutional structure, indices related to "corporate governance" (GOVERNANCE), "internal control" (INTERNAL), and "managerial structure" (MANAGERIALST) were adopted and weighted from the benchmark sets of [5], [31], and [7]. These variables add the rule-sets and policies governing key decisions and reporting quality to the model; evidence suggests that greater transparency and greater independence of the board or internal committees help reduce operational risks [5, 7, 31]. In addition, “corporate social responsibility” (CSR) and the “firm information environment” (INFOFIRM) were treated as critical variables for completing a holistic ERM perspective, as reflections of a firm’s engagement with stakeholders and its access to internal and external information; these components affect the firm’s capacity for rapid crisis response and the alignment of strategic agendas [5, 7].

Beyond these, two senior-management-level indicators were added to the model: “CEO efficiency” (MANAGEREFF) and CEO personality traits (MANAGERCH), extracted from [13]. These factors indicate the extent to which risk-taking decisions are influenced by top management’s experience, skill, optimism, or short-term orientation. In parallel, “board characteristics” (BOARDCH) and “audit attributes” (AUDITORCH), presented by [12] and [8], were employed as indicators of supervisory structure and the quality of external control. Finally, “firm life cycle” (CYCLE) from [29] was added to account for the effect of a firm’s development or maturity stage on its risk-management capability. By combining these 18 variables grounded in reputable domestic and international research, the developed model attains higher capacity to analyze and predict ERMI accuracy and serves as a robust tool for financial and accounting decision-makers in listed companies. Accordingly, after implementing the meta-synthesis method, the developed model of this study is as follows:

ERMI_i = f(Size_i · Leverage_i · ROA_i · Salesgrowth_i · Div_Ind_i · GRAWOP_i · MKTBK_i · INTRATE_i · OPEFFE_i · GSM_i · TAX/REV_i · TAXRISK_i · GOVERNANCE_i · INTERNAL_i · MANAGERIALST_i · CSR_i · INFOFIRM_i · MANAGEREFF_i · MANAGERCH_i · BOARDCH_i · CAPSTR_i · AUDITORCH_i · CYCLE_i)

Stage Three: Evaluating the Accuracy of the New Model Using a Perceptron Neural Network

In this stage, as in Stage One, the perceptron method was used. The variables of this study are presented below. This relation indicates that the value of the enterprise risk management index for each firm is calculated as a function of a set of financial, operational, and institutional variables. In this model, firm size and the debt ratio reflect the structure of resources and financial obligations; profitability and sales growth reflect operational efficiency and the firm’s capability to generate revenue; and the dividend payout ratio represents policies for redistributing cash resources. In addition, growth opportunities, the market-to-book ratio, the risk-free rate, and operational efficiency incorporate investors’ outlook and the stability of production and service processes into the firm’s risk assessment. Stock market growth represents the mobility and liquidity of a firm’s shares, and tax revenue volatility along with tax risk indicate the likelihood of regulatory changes and instability in cash flows. In another part of the function, corporate governance, internal control, and managerial structure measure the quality of decision-making and organizational oversight. Corporate social responsibility and the firm’s information environment reflect the capacity to align with stakeholder expectations and access internal and external data. Moreover, CEO efficiency and personality, board characteristics, capital structure, and audit process attributes reveal how individual and institutional factors influence risk management. Finally, the firm life cycle accounts for the organization’s stage of maturity or nascency and timestamps the maturity of risk-management structures. The combination of these variables provides a comprehensive function that can play a decisive role in the precise analysis and prediction of the enterprise risk management index [36].

Data Extraction

In the data-extraction stage, an initial list of 102 companies listed on the Tehran Stock Exchange was compiled, and for each firm, the values of 18 financial, operational, and institutional variables—including the baseline ERMI model variables and the newly defined components (including growth opportunities, market-to-book ratio, risk-free rate, operational efficiency, stock market growth, tax indices, corporate-governance dimensions, internal control, managerial structure, corporate social responsibility, information environment, managerial and board characteristics, capital structure, audit attributes, and firm life cycle)—were extracted. All values were organized into a panel data structure with 816 rows (corresponding to annual observations for each firm) and then mapped to the interval [0, 1] using the Min-Max normalization method so that the scale and range of variables would be uniform and comparable. This integrated, preprocessed dataset formed the basis for training and validating the perceptron network model to predict the enterprise risk management index with precision.

Partitioning Data into Training and Test Sets

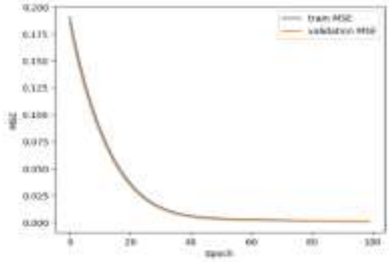
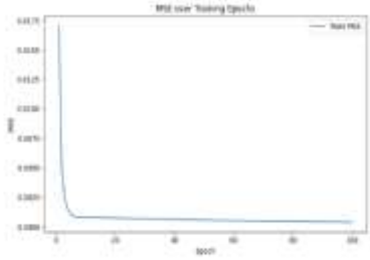
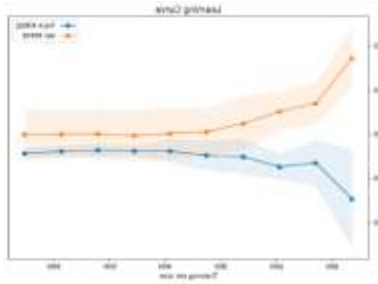
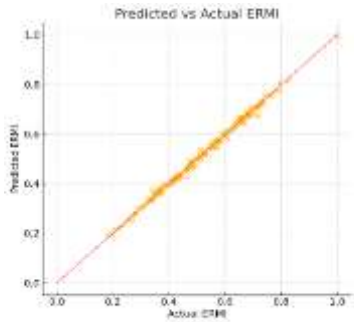
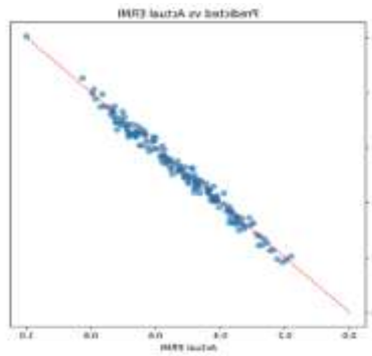
During data preprocessing, the normalized panel dataset comprising 816 observations was first randomly split—using a fixed random seed—into two parts: 80% of the observations for training the model and the remaining 20% for testing its final performance. This random split ensures that the training samples represent the diversity of the full dataset while the model is also evaluated against “unseen” data. Keeping the random seed fixed enables researchers and other interested parties to exactly reproduce the same training–test composition in future runs.

Perceptron Model Design

This study employed a simple perceptron architecture to predict the ERMI index, consisting of one input layer with the number of neurons equal to the number of features (23 variables) and a single-neuron output layer with a linear activation function. Selecting a linear activation at the output enables an exact equivalence between the perceptron and the classical linear regression of Hoyt and Liebenberg (2011), with the output-layer weights directly serving as regression coefficients. This minimalist architecture, while easy to implement, allows automatic parameter optimization via a gradient-descent algorithm (Adam) and monitoring of the learning trajectory, and it avoids the complexity of multilayer networks so that the analysis of each variable’s influence on ERMI prediction remains transparent.

The MSE value of 0.000422 indicates that the mean squared difference between actual and predicted ERMI values is very small. Given that the data were normalized within the range [0,1], this MSE value clearly demonstrates the high accuracy of the perceptron model, as the squared errors remained at the order of 10^{-4} and prevented severe error dispersion. The root mean squared error (RMSE) equals 0.0205, representing the model’s average absolute error in ERMI units. In other words, the model’s predictions deviate on average by only 0.02 units from the actual ERMI values. This small number indicates a high ability to reproduce the enterprise risk management index with precision and shows that the model, in addition to being low-error, also has stable performance.

Next, in line with the objective of comparing the base-stage model with the developed model, related charts are presented.

Index	Base Model	Developed Model
MSE	0.0008	0.000422
MSE Curve During Training		
Learning Curve of the Model		
Predicted vs. Actual ERMI Values Plot		

In this research, two modeling structures for predicting the enterprise risk management index were examined. The base model employed only five central financial features, including firm size, leverage ratio, return on assets, sales growth, and dividend payout ratio. In contrast, the developed model included these five variables plus eighteen new components: operational growth opportunities, market-to-book equity ratio, risk-free interest rate, operational process efficiency, stock market growth, tax revenue volatility, tax risk from fiscal policies, corporate governance dimensions, level of internal controls, managerial structure, corporate social responsibility, quality of the firm's information environment, CEO efficiency, CEO personality traits, board characteristics, capital structure, audit process quality indices, and firm life cycle stage. By incorporating these enriching components, the developed model was able to cover diverse financial, operational, and institutional dimensions in analyzing and predicting the organizational risk index more precisely.

Both models were trained in Python using a perceptron neural network. The panel dataset of 816 observations was split in an 80/20 ratio, and after normalization within [0,1], the network was trained for 100 epochs with a batch size of 16 and optimized with the Adam algorithm. Results showed that the base model, after training, had MSE ≈ 0.00080 and RMSE ≈ 0.0283, whereas the developed model reduced MSE to 0.000422 and RMSE to 0.020548. This significant reduction (over 47% in MSE and more than 27% in RMSE compared to the base model) confirms that adding institutional and operational components improved the model's ability to reproduce the ERMI index more accurately. In the error-curve visualization, the base model with an initial MSE of ≈0.18 experienced a rapid decline to 0.005 within 40 epochs and then gradually approached near zero. The developed model also showed an initial sharp decline, but then the training and validation sets stabilized with minor differences around MSE ≈ 0.0004. This indicates that with richer data, the network converges faster and achieves lower final error.

The learning curves of both models confirmed that adding features not only reduced error but also decreased the downward slope of the validation RMSE across different data sizes. In the developed model, validation RMSE declined from about 0.0124 at low sample size to 0.0122 at full data size, while in the base model the gap between training and validation errors was slightly larger. The scatter plot of predicted versus actual values also showed greater clarity: in the base model, points were distributed near the 45-degree line but with several outliers outside central zones, whereas the developed model placed nearly all points with small deviations around the ideal line, demonstrating a more homogeneous concentration of accuracy. The residuals plot also highlighted performance differences; in the base model, residuals were distributed around zero up to ±0.05, but in the developed model this distribution was limited to ±0.02 with no systematic pattern of error increase at specific points. This indicates that the developed model not only has a lower mean error but also improved error stability and substantially reduced the likelihood of severe errors. Overall, the comparison of the two structures demonstrates that including new variables from the literature and from institutional and financial functions, in addition to emphasizing the base model's core aspects, significantly enhances predictive performance.

In the final evaluation table, Model 1, which included only five features, reached MSE ≈ 0.0097 and MAE ≈ 0.0807 and was able to explain about 18.65% of the variance in ERMI ($R^2 \approx 0.1865$). This relatively low R^2 indicates that the five features alone do not provide an adequate approximation of the response.

Model 2, with 18 features, performed much better: MSE ≈ 0.0084, MAE ≈ 0.0708, and $R^2 \approx 0.7575$. This $R^2 = 0.7575$ indicates that more than 75% of the variance in ERMI is explained by these features. This large improvement in R^2 confirms that adding various managerial and financial variables significantly enhances predictive power.

Table 4. Comparison of the Models Examined Using Neural Networks

Model	Input Features	Output	MSE	MAE	R^2	Convergence Point
Base Model	5 features	ERMI	0.0097	0.0807	0.1865	~20 epochs
Developed Model	18 features	new ERMI	0.0084	0.0708	0.7575	~20–30 epochs

To ensure the reliability of the results, the Wilcoxon test was also employed. The results of this test are presented in the following table.

Table 5. Wilcoxon Test

Index	Value	Interpretation
Total N	816	Number of observations (e.g., firms across different periods)
Test Statistic	167413	Sum of positive and negative ranks after calculating differences (main test value)
Standard Error	201.8647	Standard error for computing standardized statistic
Standardized Test Statistic (Z)	-9.448	Normalized statistic for Wilcoxon—indicates how strong and significant the difference is
Asymptotic Sig. (2-tailed)	0.000	Significance level of the test—p-value

In this test, since $p = 0.000$ (rounded, actual < 0.001), and this value is less than 0.05, the test result is significant. This means that there is a significant difference between the predicted results of the two models (base and developed). Moreover, since the Z value is negative and very large (-9.448), it indicates that in most cases, the developed model performed better (with lower error and higher accuracy compared to the base model).

4. Discussion and Conclusion

The findings of this study demonstrate that extending the baseline ERM model with a broader set of financial, operational, and institutional variables significantly enhances its predictive accuracy. The reduction in mean squared error (MSE) and root mean squared error (RMSE), coupled with the increase in R^2 to 0.7575, indicates that a more comprehensive risk framework not only reduces error variance but also provides greater explanatory power. This confirms that risk in organizations is inherently multidimensional and cannot be adequately captured by limited financial indicators such as firm size, leverage, return on assets, sales growth, or dividend payout ratios [1, 21]. By including institutional, governance, and operational factors, the extended model represents a more holistic approach to ERM that resonates with the complex realities of contemporary firms operating in uncertain environments [6, 10].

One of the most notable results is the evidence that variables relating to governance and internal organizational structures meaningfully contribute to predictive improvements. Characteristics such as board diversity, CEO power, and audit committee composition create conditions that either mitigate or amplify enterprise risk. Prior studies highlight that gender diversity on boards reduces systematic risk by improving monitoring and decision-making [12], while excessive CEO power may increase the likelihood of stock price crash risks [13]. Our findings align with these arguments by showing that incorporating such governance-based indicators into ERM not only strengthens explanatory power but also reduces the probability of extreme errors. Similarly, studies demonstrate that audit committee quality affects the timeliness and credibility of risk disclosures, thereby shaping investor perception and market risk [8]. The consistency between our results and these earlier findings underscores the necessity of integrating governance proxies into ERM modeling.

Operational performance factors also emerged as critical contributors in the extended model. Variables such as operational efficiency, opportunities for operational growth, and stock market growth contributed substantially to reducing prediction errors. This finding aligns with research indicating that supply chain disruptions and operational bottlenecks can escalate into systemic risks, particularly in interconnected industries [2]. It also supports arguments that operational resilience and digital readiness are vital determinants of firm survival and performance during crisis events such as the COVID-19 pandemic [9]. The inclusion of operational risk factors provides a richer perspective on how firms manage volatility beyond traditional financial ratios. For example, in Industry 4.0 contexts, information system security practices and cyber supply chain management are directly tied to risk and performance outcomes [10]. Thus, our findings support and extend this stream of literature by empirically validating that operational dimensions strengthen ERM predictability.

Financial market-related indicators also played a significant role. The inclusion of the market-to-book ratio as a proxy for investor expectations improved model outcomes by capturing the forward-looking valuation of firms. This finding supports the work of [14], who emphasized that firm characteristics directly influence systematic risk exposures. Similarly, incorporating tax volatility and tax policy risk proved essential. This aligns with [15], who highlighted the impact of tax risks on firm value. Such results indicate that fiscal policy and investor sentiment are not peripheral but central to enterprise risk measurement. Additionally, the importance of the risk-free interest rate variable confirms that macroeconomic fundamentals significantly shape firm-level risk, consistent with [16], who emphasized the interdependencies between asset-liability structures and systemic risks in banks.

The results also reveal that corporate social responsibility (CSR) and the quality of firms' information environments improve ERM predictability. This is consistent with [7], who found that CSR influences real earnings management and pre-trust managerial behavior, both of which have implications for organizational risk. The ability of CSR to strengthen stakeholder trust and reduce reputational risks provides empirical support for its inclusion as a risk predictor. Similarly, research by [5] demonstrated that information quality management criteria directly influence firm transparency and thereby risk assessments, findings echoed in our study through the significance of information environment variables. These factors capture the broader institutional landscape in which firms operate, indicating that ERM models must account for stakeholder relationships and information asymmetries.

Cross-country evidence reinforces these insights. In SMEs in Malaysia, ERM adoption has been shown to depend heavily on managerial perception and resource availability [3], while in Czech firms, foreign capital has improved ERM quality [18, 19]. Similarly, studies in African contexts reveal that the relationship between ERM and sustainability is contingent on governance quality and regulatory oversight [4, 20]. Our study's emphasis on institutional and governance variables resonates with these international findings by showing that ERM effectiveness is mediated by institutional conditions. Moreover, the evidence from Iranian firms, which highlights both challenges and benefits of ERM adoption [21, 24], underscores the importance of tailoring ERM models to specific market contexts. Our study extends these insights by presenting a context-aware model that integrates institutional, fiscal, and governance elements alongside financial fundamentals.

The methodological approach of this study also aligns with broader advances in ERM analytics. By employing neural networks, we captured non-linear relationships and interactions that linear regression models such as the Hodnett and Liebenberg baseline could not fully explain [1]. The predictive gains of our extended model confirm the argument of [11] that machine learning and predictive analytics are powerful tools in financial risk management. Similarly, simulation-based approaches, such as multi-agent models [26, 27] and quasi-random sequence methods [28], emphasize the importance of computational intelligence in risk modeling. Our findings resonate with these perspectives by showing that algorithmic tools like perceptron networks can significantly enhance the accuracy of ERM predictions, especially when combined with a rich set of explanatory variables.

The evidence also corroborates arguments that ERM is a multidimensional construct linked to performance, competitive advantage, and long-term sustainability. [23] demonstrated that ERM strengthens firm performance when mediated by financial literacy and competitive advantage, while [37] found that strategic risk management improves performance in state corporations. The strong explanatory power of our extended model aligns with these findings by showing that a comprehensive ERM system incorporating governance, operational, and financial dimensions is more predictive of performance outcomes. Similarly, [17] showed that risk management influences sustainable marketing orientation, reinforcing the idea that ERM affects not only financial outcomes but also strategic positioning and stakeholder trust.

The results also provide support for studies emphasizing life-cycle effects. Our inclusion of a firm life-cycle variable, supported by the findings of [29], revealed that the maturity stage of firms shapes their risk profile and management effectiveness. Younger firms may face higher risks due to less established governance and resource systems, while mature firms benefit from stable processes but may be exposed to risks of inertia. Such dynamics illustrate the need for flexible ERM systems that account for temporal changes in organizational development.

Overall, the results show that integrating governance, operational, market, fiscal, and institutional variables with traditional financial ratios substantially improves the explanatory and predictive performance of ERM models. This multidimensional approach is consistent with recent literature across diverse contexts, from supply chain disruption modeling [2] to CSR and disclosure studies [7, 8], and from simulation-based methods [26, 27] to dynamic system modeling in banking [16]. The alignment of our results with this broad body of literature indicates that ERM is most effective when treated as an integrative framework, capturing financial and non-financial dimensions of organizational risk.

Despite its contributions, this study is not without limitations. First, while the extended ERM model integrates a wider range of variables, the dataset was limited to firms listed on the Tehran Stock Exchange, which constrains the generalizability of the findings to other contexts. Institutional, cultural, and regulatory differences across markets may limit the transferability of the model to global settings. Second, although neural networks provided significant predictive improvements, their "black box" nature can reduce interpretability compared to linear regression models. This may challenge stakeholders who require transparent and auditable decision-making tools. Third, the study employed secondary data, which inherently carry limitations related to data quality, reporting standards, and potential biases in disclosure. Finally, the cross-sectional nature of the dataset may not fully capture temporal shifts in risk management effectiveness, particularly during periods of macroeconomic turbulence.

Future studies could expand this research in several directions. First, cross-country comparative studies should be conducted to test the model's robustness across different institutional and regulatory environments. Such comparisons would shed light on how governance quality, fiscal regimes, and market structures influence ERM effectiveness. Second, future work could employ hybrid approaches that combine neural networks with interpretable machine learning techniques such as decision trees or SHAP values to enhance both predictive accuracy and transparency. Third, qualitative studies involving interviews with managers, auditors, and regulators could complement the quantitative results by revealing how institutional pressures and organizational culture affect ERM adoption. Additionally, longitudinal designs could track how firms' ERM maturity evolves over time and how shifts in regulatory and economic conditions reshape predictive relationships. Finally, integrating environmental, social, and governance (ESG) factors and cyber risk indicators could further enrich the model, aligning it with emerging global priorities.

From a practical standpoint, managers and policymakers should recognize that ERM is not merely a financial control system but a holistic governance and operational framework. Organizations should embed ERM into corporate strategy by linking it to governance structures, CSR commitments, and information quality initiatives. Boards should ensure diversity, audit committee strength, and clear accountability mechanisms to reduce risk exposure. Firms should also leverage predictive analytics and machine learning to improve the accuracy of risk forecasts, while maintaining interpretability for stakeholders. At the same time, tax risk management, operational efficiency, and life-cycle stage assessments should be incorporated into decision-making processes. Finally, regulators and policymakers can use the insights from the extended ERM model to design frameworks that encourage comprehensive risk disclosure and institutional resilience, thereby reducing systemic vulnerabilities in the market.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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