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Designing a Comprehensive and Integrated Competitive Intelligence Model Using Machine Learning for Predicting Competitors' Behavior in the Insurance Industry

ABSTRACT

In the face of a dynamic, complex, and uncertainty-filled competitive environment—particularly with economic, technological, and regulatory uncertainties—in dynamic industries such as the insurance sector, organizations require tools that go beyond traditional analysis and decision-making methods to ensure survival and growth. The present study aims to design a comprehensive competitive intelligence model with a machine learning approach in Iran's insurance industry, specifically focusing on Parsian Insurance Company. The model seeks to predict competitors' strategic behavior and provide strategic recommendations, striving to shift the organization from a reactive to a proactive position. The proposed model is designed as a systemic framework comprising five main subsystems: (1) data collection and preprocessing, (2) modeling and predicting competitors' pricing behavior using multilayer perceptron (MLP) neural networks, (3) a scenario knowledge base utilizing cross-impact analysis and K-Modes clustering, (4) identification of the current state and alignment with environmental scenarios through the K-NN algorithm, and (5) provision of strategic recommendations based on prescriptive artificial intelligence principles. The research findings indicated that the designed model, with a very high accuracy in predicting competitors' pricing behavior (correlation coefficient exceeding 0.99), and the ability to integrate prediction outputs with future-oriented scenarios, provides an effective platform for strategic decision-making under uncertainty. Moreover, by creating a link between data-driven analysis, scenario planning, and recommender systems, this model offers a practical framework for enhancing organizational competitive intelligence. From a theoretical perspective, the study fills existing gaps in the competitive intelligence literature by presenting an integrated systemic framework and applying advanced machine learning algorithms, providing an operational model for implementation in data-driven organizations. From a practical perspective, the proposed model can be used as an intelligent decision support tool in the insurance industry and other competitive industries.

Keywords: Competitive intelligence, machine learning application, competitor behavior prediction, insurance industry

Introduction

In today's volatile, uncertain, complex, and ambiguous (VUCA) business environment, organizations are increasingly challenged to navigate competitive landscapes characterized by rapid technological advancements, shifting regulatory frameworks, and dynamic market conditions. The insurance industry, in particular, operates within a high-stakes environment where strategic decisions must be informed by accurate, timely, and comprehensive intelligence about competitors' behaviors and market trends. Competitive Intelligence (CI), defined as the systematic process of gathering, analyzing, and

applying information about competitors and the external business environment to support strategic decision-making, has emerged as an indispensable component of strategic management in such industries [1, 2].

Traditional approaches to CI have relied heavily on manual data collection, descriptive analytics, and subjective interpretation of market signals. While these methods provide valuable insights, they often lack the predictive power and adaptability required in rapidly evolving contexts [3, 4]. The advent of advanced data analytics and machine learning (ML) offers transformative potential in this regard, enabling the transition from reactive to proactive intelligence systems capable of anticipating competitors' strategies and market shifts [5, 6]. In the insurance sector, where pricing strategies, product offerings, and regulatory compliance are highly sensitive to external variables, such predictive capabilities are critical for sustaining competitive advantage [7, 8].

The integration of ML into CI frameworks allows for the processing of vast, heterogeneous datasets—ranging from structured numerical data to unstructured textual sources—to identify patterns, correlations, and anomalies that may elude traditional analytical methods [9, 10]. For example, algorithms such as multilayer perceptrons, gradient boosting machines, and clustering techniques can be employed to forecast competitors' pricing adjustments, detect emerging market trends, and cluster possible future scenarios based on cross-impact analysis [11, 12]. This predictive orientation not only supports strategic agility but also aligns with the broader trend toward data-driven decision-making in insurance and other financial services [13, 14].

Several studies underscore the growing role of explainable artificial intelligence (XAI) in enhancing the interpretability and trustworthiness of ML-driven CI systems [13, 15]. In highly regulated sectors like insurance, where strategic decisions have significant economic and societal implications, decision-makers must be able to understand and justify the rationale behind model outputs [16, 17]. This is particularly relevant when using predictive models to recommend strategic responses to competitor behavior, as transparency fosters organizational trust and regulatory compliance.

The application of ML in strategic insurance decision-making is evident in various domains. For instance, regression frameworks have been developed to predict health insurance premiums based on customer demographics and risk factors [18], while hybrid tree-based models have been applied for short-term insurance claims forecasting [19]. Similarly, deep learning approaches have been leveraged for claims triage, integrating external environmental data such as weather patterns to optimize resource allocation [15]. These examples illustrate the breadth of ML applications in insurance and highlight their adaptability to competitor behavior prediction.

In parallel, scenario planning has proven to be a robust methodology for addressing uncertainty in strategic contexts. Originating in military and corporate strategy, scenario planning enables organizations to explore a range of plausible futures and develop strategies resilient to diverse environmental conditions [11]. By integrating ML with scenario planning, it becomes possible to enhance the precision of scenario generation and clustering, enabling the identification of "strong scenarios" that are internally consistent and strategically actionable [12, 20]. This hybrid approach aligns with the need for proactive strategic planning in the insurance sector, where small shifts in macroeconomic indicators or regulatory changes can have disproportionate effects on competitive dynamics [21, 22].

From a global perspective, insurers are increasingly adopting innovation strategies to strengthen competitiveness. In Kenya, for instance, firms have implemented differentiated service offerings, technology adoption, and market diversification as key competitive strategies [3, 8]. In Indonesia, strategy formulation for general insurance firms has emphasized

competitive advantage through operational efficiency and customer-centric approaches [21]. These strategic imperatives resonate with the challenges faced by Iranian insurers such as Parsian Insurance Company, which must balance local market dynamics with global trends in digital transformation and regulatory alignment [16, 23].

The predictive modeling of competitor behavior necessitates the integration of both internal and external data sources. Internal datasets may include historical pricing, product performance, and sales channel efficiency, while external data can encompass macroeconomic indicators, competitor announcements, and industry regulatory updates [24, 25]. By applying algorithms such as K-modes clustering—particularly suited for qualitative and categorical scenario variables—insurance companies can segment potential futures into distinct strategic clusters, facilitating tailored response plans [12, 19]. The quality of these clusters can be quantitatively assessed using metrics such as the Davies–Bouldin index, ensuring that scenario groupings are both meaningful and actionable [9].

Moreover, the practical implementation of ML-driven CI systems in insurance must account for ethical considerations, particularly regarding data privacy, algorithmic bias, and transparency [5, 17]. Given the sensitive nature of customer and competitor data, insurers must establish robust governance frameworks for data acquisition, storage, and processing. Explainable models, bias detection tools, and compliance monitoring systems can serve as safeguards against misuse and ensure adherence to both local and international regulatory standards [6, 13].

Despite the promising potential of ML in CI, several challenges remain. Data quality and availability are persistent barriers, particularly in markets where digitization is incomplete or fragmented [7, 10]. Additionally, the interpretability of complex models—such as deep neural networks—can be limited without dedicated XAI techniques, which may slow adoption among decision-makers accustomed to more transparent analytical frameworks [9, 13]. The resource-intensive nature of model training and maintenance, combined with the need for specialized expertise, further underscores the importance of aligning technical capabilities with strategic objectives [2, 5].

Within this context, the present study addresses the gap in the literature by proposing a comprehensive and integrated CI model that combines advanced ML techniques with structured scenario planning to predict competitors' pricing strategies in the Iranian insurance industry, focusing on Parsian Insurance Company as a case study.

Methods and Materials

This study was conducted using a mixed methods approach and based on an exploratory sequential design, implemented in three main phases. First, adopting a qualitative approach and using the case study method, the key components of competitive intelligence in Iran's insurance industry were identified. Parsian Insurance Company was selected as the primary case study, and data were collected through semi-structured interviews with 10 senior managers, analysis of organizational documents, and structured field observations. The qualitative data were analyzed using Straussian grounded theory, and key concepts were extracted through open, axial, and selective coding.

In the second phase, the qualitative findings were quantified within the framework of multi-criteria decision-making methods. Initially, using fuzzy analytic hierarchy process (FAHP), the identified variables (44 initial components) were weighted, and 21 final variables were selected. Then, causal relationships among the variables were mapped through interpretive structural modeling (ISM) and cross-impact analysis. The output of this stage was the design of the scenario knowledge base, implemented using Expert Choice, MICMAC, and Scenario Wizard software, along with the K-Modes

clustering algorithm in Python. The database included structured scenarios containing key variables, strategic actions, potential consequences, and the impact weight of each scenario.

In the third phase, to design the learning and competitor behavior prediction system, machine learning algorithms were applied within the CRISP-DM process framework. Input data included 13 years of historical pricing information from competing companies across five insurance product lines, macroeconomic indicators, insurance regulations, and the quantitative outputs from the previous phase. After preprocessing—which involved normalization, removal of outliers (using the IQR method), feature engineering, and data cleaning with the Kalman filter—the models were trained using various algorithms such as multilayer perceptron (MLP) with the Levenberg–Marquardt method, XGBoost, and LightGBM. Furthermore, to identify the scenario matching the company's current status, the k-nearest neighbors (k-NN) algorithm was applied using Euclidean distance.

In the final step, the strategic recommendation subsystem was designed using a prescriptive artificial intelligence (Prescriptive AI) approach, which, based on the model outputs, provided recommendations for pricing policies, new product design, and responses to competitors' movements.

The validity of the instruments was assessed using the content validity ratio (CVR > 0.78) and expert confirmation, while the reliability of the questionnaires was verified through Cronbach's alpha coefficient of 0.8 and the test–retest method. For the machine learning models, cross-validation and performance metrics such as RMSE, MAE, and MAPE were used for evaluation. The research design complied with international standards, including COREQ (qualitative section) and TRIPOD-AI (quantitative and predictive section), and in line with reproducibility principles, the models were implemented as executable Python code in a cloud environment.

Findings and Results

At this stage of the study, by analyzing the relationships between key variables, a set of the most probable future scenarios for Parsian Insurance Company is identified. This scenario bank will serve as a framework for formulating operational strategies and implementation plans appropriate to each future state.

Considering the broad dimensions of the study variables and the range of variation in each indicator, the potential scenario space derived from the combination of these variables is calculated as follows:

Where *di* represents the number of levels for each variable. With the eight variables selected by experts for this section, the scenario space results in $3 \times 3 \times 3 \times 3 \times 4 \times 4 \times 3 \times 3 = 11{,}664$ scenarios. The specialized scenario-building software, utilizing advanced computational algorithms, enables the screening of this extensive set and the extraction of three categories of scenarios:

1. High-probability scenarios
2. Low-probability scenarios
3. Scenarios with high consistency and adaptability

Based on the theoretical foundations of network analysis, three key indicators have been designed for evaluating scenarios:

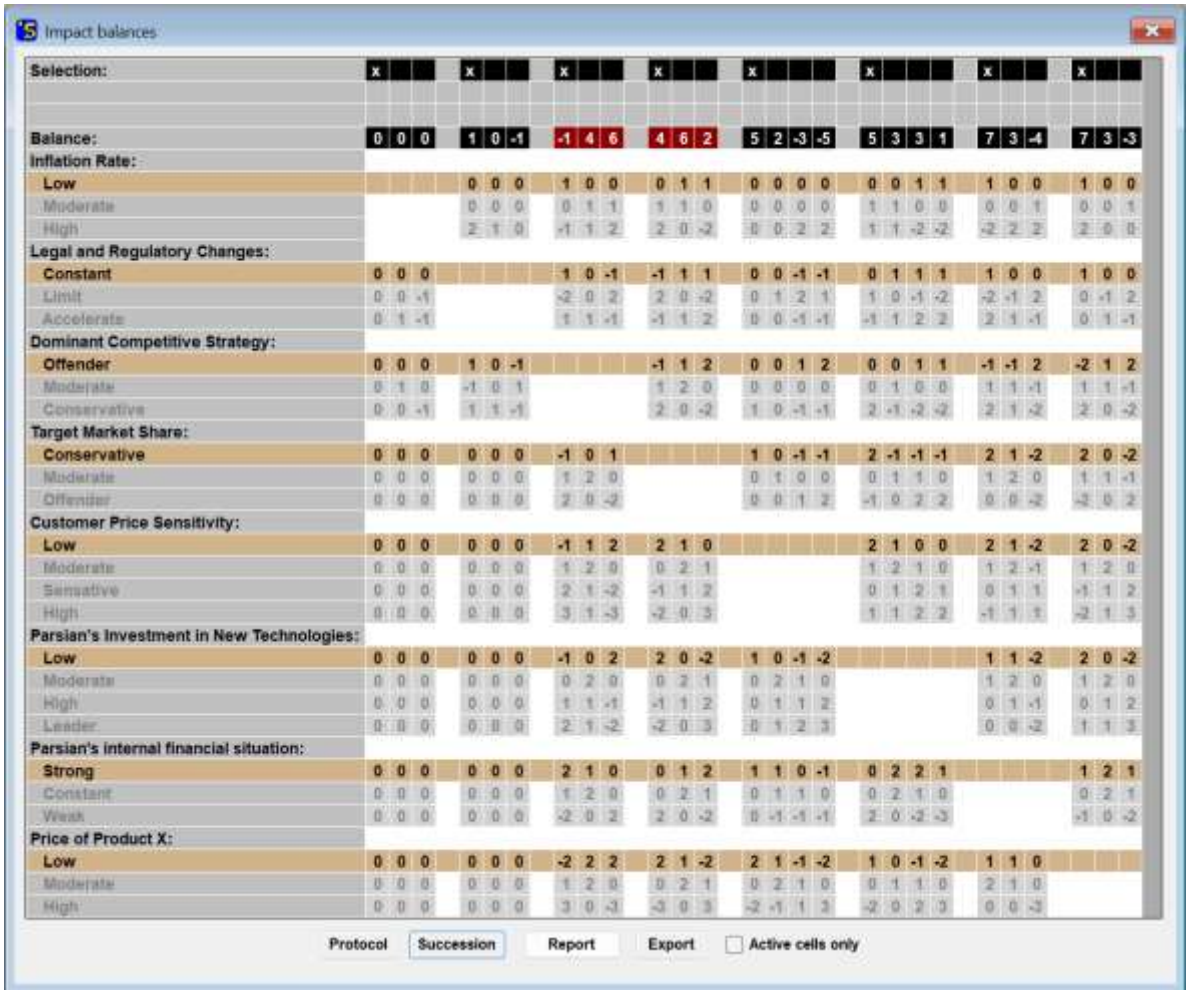
Total Synergetic Impact (TSI): Where *Ij* denotes the impact score of the *j*-th state. This index serves as a measure of the overall credibility and plausibility of a scenario.

Descriptor Inconsistency Index (DII): This index measures the difference between the maximum possible score and the selected score for each descriptor. If this value becomes negative, that descriptor is considered inconsistent within the scenario.

Scenario Inconsistency Index (SII): This index reflects the maximum inconsistency value among all descriptors in a scenario. A value of zero for this index indicates a "strong scenario," meaning that no descriptor exerts a negative effect.

Figure 1.

Output of Scenario Wizard Software



Scenarios for which both SII and DII equal zero are classified as strong scenarios, possessing the highest "total impact scores" and "zero inconsistency." During the analysis process, the software successfully identified 10,000 strong scenarios from among the possible states.

In the final stage, the selected scenarios are grouped into homogeneous clusters. This classification is based on shared scenario characteristics and the degree of similarity in their impact patterns. The outcome of this process enables decision-makers to develop strategic solutions tailored to each scenario group. This systematic approach facilitates the selection of the most optimal operational strategies in response to potential future conditions.

The breadth and vast dimensions of the probable scenarios facing Parsian Insurance Company make the operational implementation of strategies based on this extensive volume of scenarios highly challenging. Therefore, in this phase of the

research, machine learning approaches were employed to classify scenarios based on their structural and contextual similarities, with the goal of identifying the main ranges of likely scenarios.

Given the nominal and discrete nature of the scenario variables, selecting an appropriate clustering approach involves certain limitations, as popular numerical data-based methods (such as K-means) demonstrate limited effectiveness for this type of data. Under such conditions, algorithms capable of handling qualitative variables and measuring similarity through specialized functions—such as simple matching—are necessary. Accordingly, the K-modes algorithm was selected as the optimal solution. This algorithm measures dissimilarity between clusters using the simple mismatch function, where a lower value indicates higher homogeneity among the cluster members (Kaufman & Rousseeuw, 1990). The function is defined as follows:

D(X, Y): the dissimilarity measure between two samples

m: the number of attributes

δ: the mismatch function, equal to 0 for identical values and 1 otherwise

Scenario data were transformed into one-hot encoding format and then fed into the algorithm. To determine the optimal number of clusters, the algorithm was executed over a range of 3 to 12 clusters, and the Davies-Bouldin index was calculated for each configuration. This index, which serves as a measure of clustering quality, is computed as follows:

$DB = (1 / k) * \Sigma \max[(Si + Sj) / d(ci, cj)]$

where: k: the number of clusters

Si: intra-cluster dispersion

d(ci, cj): distance between cluster centers

Based on the results obtained, 3 clusters were identified as the optimal structure, displaying the lowest Davies-Bouldin index values. This classification enables more focused scenario analysis and the formulation of effective operational strategies.

Scenario Grouping and Analysis: A total of 12 consistent scenarios were identified. An analysis of the state combinations allows for their classification into several main groups:

Group 1: Stability and Conservatism Scenarios (Scenarios 1, 2, 3, 4)

Shared Characteristics: Dominant Competitive Strategy: Conservative

Target Market Share: Conservative

Customer Price Sensitivity: Low

Parsian’s Investment in New Technologies: Low

Price of Product X: Low (moderate competition / value-focused)

Differences: Inflation Rate (Low/Moderate), Legal Changes (Constant/Limited), Parsian’s Financial Status (Strong/Constant)

Analysis: These scenarios depict a future in which the external environment (industry competition, customer sensitivity, product X pricing) remains relatively calm and favorable. Insurance companies adopt conservative strategies, and customers show low price sensitivity. In response, Parsian Insurance also adopts a conservative approach in market share targeting and technological investments. Parsian's financial condition is strong or stable in these scenarios, which appears logical. This group of scenarios represents a stable and low-turbulence future for the insurance industry and Parsian Insurance.

Total impact score: Relatively low (48 to 52), which may indicate fewer strong (positive or negative) interactions among states in this stable environment.

Consistency value: All are 0, indicating complete internal consistency among the state combinations.

Group 2: Moderate Change Scenario (Scenario 5)

Distinctive Characteristics: Inflation Rate: Moderate

Legal and Regulatory Changes: Accelerated

Dominant Competitive Strategy: Moderate

Target Market Share: Moderate

Customer Price Sensitivity: Moderate

Parsian's Investment in New Technologies: Moderate

Parsian's Internal Financial Situation: Constant

Price of Product X: Moderate (moderate price competition)

Analysis: This scenario represents a "middle scenario" where most variables are at moderate or median levels. Legal changes are facilitative, competition is balanced, customer sensitivity is moderate, and Parsian exhibits a moderate approach and financial status. This scenario illustrates a future that is neither highly favorable nor unfavorable but one characterized by manageable and gradual changes.

Total impact score: 60. This value is higher than in Group 1 and may indicate greater dynamism and stronger reinforcing interactions in a moderately changing environment.

Consistency value: 1. This is the only scenario with a value of 1, suggesting the presence of a minor inconsistency or tension in the combination of states; however, the software still deemed it sufficiently consistent.

Group 3: High Competition and High Sensitivity Scenarios (Scenarios 6, 7, 8, 9, 10, 11, 12)

Shared Characteristics: Dominant Competitive Strategy: Aggressive

Target Market Share: Aggressive

Customer Price Sensitivity: High

Price of Product X: High (intense price competition / price war)

Legal and Regulatory Changes (mostly): Constant

Differences: Inflation Rate (Low/Moderate/High), Parsian's Technological Investment (High/Leader), Parsian's Financial Status (Strong/Constant)

Analysis: This larger group of scenarios envisions a significantly different and highly challenging future for Parsian and the insurance industry. The external environment is intensely competitive (aggressive, price wars), and customers are highly price-sensitive. In response, Parsian adopts ambitious market share goals and high levels of technology investment (possibly aimed at improving efficiency or introducing new services to counter competition). Parsian's financial condition is Strong or Constant in these scenarios; reaching the Strong status in such a competitive setting would be a major challenge and may only be assumed under exceptional success in competition and technology (as seen in Scenarios 6 and 10).

Total impact score: Values range from 53 to 60, generally higher than in Group 1. This is logical, as in an intensely competitive environment, different states (such as high sensitivity, aggressive strategies, high technology investment) tend to interact more and reinforce one another.

Consistency value: All are 0, except for Scenario 5 which is outside this group. This indicates that even these “difficult” combinations are considered consistent according to the input matrix.

The software output identified 12 logically possible scenarios from all possible state combinations. These scenarios clearly illustrate three main clusters of probable futures:

1. **Stable and low-competition futures:** Where the external environment is relatively calm, and Parsian adopts a conservative approach (Scenarios 1–4).
2. **Highly competitive and challenging futures:** Where the environment is intense and price-driven, and Parsian must adopt more aggressive strategies (in market targeting and technology) to survive or grow (Scenarios 6–12).
3. **A moderate scenario:** Reflecting a future with manageable and moderate changes (Scenario 5).

By leveraging the output of the “Scenario Wizard” tool and integrating it with localized knowledge and industry expertise, three key scenarios are selected, analyzed, and their implications for Parsian Insurance Company are explored. Ultimately, strategic options appropriate to each scenario are proposed to enable proactive planning and response to future uncertainties.

4.2. Selection of Key Scenarios

Among the 12 scenarios extracted from the Scenario Wizard tool—all exhibiting high internal consistency (Consistency values of 0 or 1)—three primary scenarios were selected. This selection was based on their coverage of a wide spectrum of probable conditions, from favorable to highly challenging, as well as a likely intermediate scenario. This approach helps Parsian Insurance prepare for a broad range of possible futures. The selected scenarios are:

1. **Scenario 1: "Stability and Cautious Growth" (Scenario No. 1):** This scenario represents relatively favorable and stable conditions in which competitive pressures are lower, and Parsian’s internal status is strong. (The relatively favorable end of the spectrum)
2. **Scenario 5: "Moderate Change and Balanced Competition" (Scenario No. 5):** This scenario is selected as the most likely intermediate case, where all variables remain at moderate and stable levels. (The median and most probable scenario)
3. **Scenario 9: "Rising Inflation and Aggressive Competition" (Scenario No. 9):** This scenario illustrates a highly challenging condition marked by high inflation and intense competitive aggression. (The challenging end of the spectrum)

Each of these scenarios will be elaborated upon in detail in the following sections, and their implications and strategic options for Parsian Insurance Company will be thoroughly analyzed.

Scenario 1: “Stability and Cautious Growth”

Key Parameters:

- Inflation Rate: Low
- Legal and Regulatory Changes: Constant
- Dominant Competitive Strategy: Conservative
- Target Market Share: Conservative
- Customer Price Sensitivity: Low
- Parsian’s Investment in New Technologies: Low

- Parsian's Internal Financial Situation: Strong
- Price of Product X: Low (referring to Parsian's key or competitive product)

Narrative Description (Scenario): In this scenario, the Iranian economy is experiencing a period of relative stability, characterized by a low inflation rate. Limited regulatory changes have created a predictable environment, with no significant modifications introduced to the legal framework governing the insurance industry. In such a climate, rival companies adopt conservative strategies, primarily focusing on maintaining their current market position rather than aggressively expanding their market share. Their attention is directed toward retaining existing customers by offering lower prices for core products such as third-party liability and vehicle insurance. This is partly because customer price sensitivity remains low, meaning that customers do not base their insurance purchasing decisions solely on price, but also consider other values such as service quality, coverage, and the company's reputation. Parsian Insurance Company enjoys a strong internal financial position in this scenario, enabling more confident planning and maneuvering. However, Parsian's investment in new technologies remains limited, with an emphasis on traditional processes and in-person services, which could potentially pose long-term challenges. The price of Product X—assumed here to be a core or high-volume product like third-party or comprehensive car insurance—is low, indicating limited competition and a focus on sustainable profitability, aimed at maintaining competitive price advantages in a relatively calm market.

Implications for Parsian Insurance Company:

Opportunities:

- **Increased Profitability and Financial Stability:** Due to low inflation and minimal aggressive price competition from rivals, profit margins are expected to improve, resulting in more predictable and stable profitability. Parsian's strong financial position reinforces this stability.
- **Focus on Quality and Non-Technological Innovation:** With price wars becoming less of a concern, the company can allocate resources to improving service quality, developing new products (not necessarily tech-driven), and enhancing customer experience.
- **Organic Growth and Customer Loyalty:** Low price sensitivity allows Parsian to grow organically and foster customer loyalty by providing added value and maintaining satisfaction among existing clients.

Challenges/Threats:

- **Technological Lag:** Limited investment in new technologies increases the risk of falling behind competitors (especially if the competitive environment changes suddenly or new technologies emerge), resulting in loss of operational advantages like efficiency and cost reduction.
- **Stagnation in Technological Innovation:** The absence of immediate pressure to innovate might lead to a decline in innovation momentum and missed opportunities for process improvement and modern service delivery.
- **Long-Term Market Share Loss Risk:** Even though competitors are currently conservative, Parsian's lack of tech investment could make it vulnerable to future market changes and rising customer expectations.

Strategic Options for Parsian Insurance Company:

1. **Preserve and Enhance Service Quality and Brand Building:** Given low price sensitivity, Parsian should focus on strengthening its brand, expanding effective sales networks, and providing differentiated after-sales services to attract and retain customers based on quality.

2. **Optimize Product Portfolio and Coverage Options:** Focus on real customer needs and innovate product design (e.g., bundled insurance, special coverage) without aggressive price reductions.
3. **Smart Management of Strong Financial Resources:** Parsian can allocate part of its robust financial resources to long-term strategic infrastructure investments, even if not urgently required now, such as:
    - **Gradual Investment in Key Technologies:** Such as artificial intelligence for risk assessment, blockchain for transparency, or digital platforms for customer interaction. These can serve as hidden competitive advantages and prepare the company for the future.
    - **Strengthen Data and Analytics Infrastructure:** To enhance pricing accuracy and gain deeper customer insights.
4. **Human Capital Development and Training:** Focus on communication skills, customer orientation, and product technical knowledge to improve customer satisfaction.
5. **Continuous Monitoring of Competitive and Technological Environment:** Even in stable conditions, Parsian should remain vigilant to changes in competitor strategies or technological emergence.

Scenario 5: "Environment with Moderate Changes and Balanced Competition"

Key Parameters:

- Inflation Rate: Moderate
- Legal and Regulatory Changes: Accelerate
- Dominant Competitive Strategy: Moderate
- Target Market Share: Moderate
- Customer Price Sensitivity: Moderate
- Parsian's Investment in New Technologies: Moderate
- Parsian's Internal Financial Situation: Constant
- Price of Product X: Moderate (referring to Parsian's key or competitive product)

This scenario represents a realistic and dynamic environment where all key parameters are at moderate levels. A moderate inflation rate forces companies to manage costs more precisely and adjust pricing strategies, though not as severely as during high inflation periods. Legal and regulatory changes are accelerating, requiring companies to be well-prepared to adapt to new compliance standards—such as mandatory insurance coverage, technical reserves, or IT regulations. The dominant competitive strategies and market share goals of rival firms are also moderate and balanced—not too conservative nor overly aggressive—indicating a healthy and balanced competitive landscape. Customer price sensitivity remains moderate, implying that clients value both price and quality. For instance, some may seek digital and personalized services, while still considering cost a key factor. In this scenario, Parsian makes moderate investments in technologies such as digital platforms and mobile applications, while maintaining a stable and consistent financial standing. The price of Product X is also at a moderate level, reflecting a balance between competitiveness and profitability. This dynamic environment offers opportunities for innovation and market expansion, though it demands careful resource management.

Implications for Parsian Insurance Company:

Opportunities:

- **Balance Between Growth and Profitability:** A moderate environment offers the potential for reasonable growth and sustained profitability, provided the company adapts effectively to ongoing changes.
- **Attracting Smart Consumers:** Customers with moderate price sensitivity seek real value. Parsian can attract them through a mix of competitive pricing and high-quality services.
- **Developing Adaptability Capabilities:** With accelerated regulatory changes and moderate tech investment, the company is encouraged to strengthen its adaptability and innovation capacities.

Challenges/Threats:

- **Pressure on Profit Margins:** Moderate inflation and balanced competition could create ongoing pressure on profit margins, necessitating constant cost optimization.
- **Regulatory Noncompliance Risk:** As regulatory changes accelerate, failure to adapt in time increases the risk of penalties or missed opportunities.
- **Need for Balanced Technology Investment:** Moderate tech investment must be optimized—not so little that the company falls behind, nor so much that it yields insufficient returns.
- **Value-Based Competition:** Rivals are also moderately competitive, so Parsian must offer strong and differentiated value propositions.

Strategic Options for Parsian Insurance Company:

1. **Flexible and Value-Based Pricing Strategy:** Instead of focusing solely on low prices, the emphasis should be on delivering "value" to the customer. This includes a combination of competitive pricing, comprehensive coverage, excellent customer service, and streamlined processes.
2. **Strengthen Regulatory Compliance Unit:** Given the accelerating regulatory environment, Parsian must establish a robust system for monitoring, analyzing, and quickly adapting to new regulations.
3. **Optimize Technological Investments:** Moderate investments in technology should be smart and goal-oriented, such as:
    - **Digitization of Internal Processes:** To enhance efficiency and reduce costs.
    - **Development of Digital Sales Channels:** To access new markets and cut distribution costs.
    - **Data Analytics for Product Personalization:** To offer more precise proposals and increase customer satisfaction.
4. **Agile Product Development:** Capability to rapidly design and launch new products or modify existing ones in response to market needs and regulatory shifts.
5. **Advanced Customer Relationship Management (CRM):** To better understand customer needs, improve experiences, and increase loyalty.

Scenario 9: “Rising Inflation and Aggressive Competition”

Key Parameters:

- Inflation Rate: High

- Legal and Regulatory Changes: Constant (often, in inflationary conditions, regulatory changes slow down due to crisis management priorities)
- Dominant Competitive Strategy: Offender
- Target Market Share: Offender
- Customer Price Sensitivity: High
- Parsian's Investment in New Technologies: High
- Parsian's Internal Financial Situation: Constant
- Price of Product X: High (refers to the price of Parsian's key or competitive product)

Narrative Description (Scenario): This scenario portrays one of the most challenging potential futures for Iran's insurance industry. The economy is grappling with a high inflation rate, which affects all dimensions of the insurance business—from increased claim costs to decreased customer purchasing power. In this environment, competitors adopt an aggressive (Offender) strategy, seeking to expand their market share at any cost, including drastic price cuts or offering irrational coverage. Their market share objectives are also aggressive, significantly intensifying the level of competition. As a result, customer price sensitivity rises sharply due to reduced purchasing power and a focus on minimizing expenses. Parsian Insurance Company, in this scenario, makes high investments in new technologies, aiming to retain part of the market by offering differentiated services. Its internal financial condition remains constant. The price of Product X is set high, reflecting an attempt to cover inflation-induced costs and focus on a niche of price-insensitive clients; however, this may reduce overall competitiveness.

Implications for Parsian Insurance Company:

Threats/Challenges:

- **Severe Pressure on Profitability:** High inflation leads to increased claim costs and operating expenses, while aggressive competition and elevated price sensitivity among customers make proportional price increases difficult. This could drastically reduce profit margins or even result in losses.
- **Price War and Market Share Erosion:** Price-based aggressive competition may drag Parsian into a damaging price war, which would harm profitability; alternatively, if Parsian avoids this competition, it risks losing market share.
- **Moral Hazard and Adverse Selection:** With extreme focus on low pricing, high-risk customers seeking the cheapest policies are more likely to be attracted, while low-risk and profitable clients may be drawn to firms offering better services.
- **Liquidity Management Challenge:** High inflation can erode the real value of investments and reserves, complicating liquidity management.
- **Uncertainty in Asset and Liability Valuation:** In an inflationary environment, the real value of the company's reserves and obligations will fluctuate unpredictably.

Opportunities (Limited but Critical):

- **Leveraging Technology Investment:** Parsian's high level of investment in technology can serve as a critical advantage in this context—such as optimizing processes, reducing costs, or improving the accuracy of risk assessment to avoid attracting high-risk clients.

Strategic Options for Parsian Insurance Company:

1. **Risk-Based Dynamic Pricing:** In an inflationary and competitive environment, pricing must rely on more precise risk assessment of each customer. Using advanced data and analytical models for dynamic pricing that can rapidly adapt to cost changes and market conditions is essential.
2. **Intensive Cost Optimization and Productivity Enhancement:** All operational processes must be reviewed to maximize efficiency. Parsian's technological investments should be used in this direction (e.g., process automation, reducing human resources in repetitive tasks, and precise claims management).
3. **Active Portfolio and Risk Management:** Focus on products with better profit margins or lower risk. Avoid price wars over low-margin, high-risk products.
4. **Diversification of Revenue and Investment Sources:** Where possible, explore opportunities for investing in inflation-resistant assets or developing new insurance products that are less affected by inflation volatility.
5. **Strategic Customer Communication:** Despite high price sensitivity, educating customers about the real value of insurance coverage—and the difference between "cheap price" and meaningful protection—can be helpful. Emphasize segments of the market that still value quality and credibility.
6. **Development of Modular and Adjustable Coverage Products:** Offering insurance policies with affordable basic coverage and optional add-ons allows customers to choose, while enabling Parsian to compete in price-sensitive markets.
7. **Full Utilization of Technological Investments:**
    - **Artificial Intelligence for Risk Analysis and Fraud Detection:** To reduce losses stemming from fraud.
    - **Automated Claims Payments:** To reduce time and administrative costs.
    - **Real-Time Market Monitoring:** To respond swiftly to competitor pricing changes.
    - **Advanced Modeling:** For more accurate forecasting of claim rates and future inflation trends.

Discussion and Conclusion

The results of this study demonstrate that the proposed comprehensive competitive intelligence model—integrating advanced machine learning algorithms, scenario-based planning, and prescriptive analytics—can accurately predict competitors' pricing behavior in the insurance industry, with a correlation coefficient exceeding 0.99. This level of accuracy, combined with the model's ability to cluster future scenarios using the K-modes algorithm and align them with the company's current market state, provides Parsian Insurance Company with a robust foundation for proactive strategic decision-making. The model's systemic structure, consisting of five interconnected subsystems, ensures that insights derived from historical pricing data, macroeconomic indicators, and competitive trends are transformed into targeted strategic recommendations, thereby bridging the gap between predictive and prescriptive analytics [11-13].

One of the most notable findings is the effective categorization of 12 high-consistency scenarios into three main strategic groups—stability and cautious growth, moderate change and balanced competition, and rising inflation with aggressive competition. This classification was achieved through a combination of cross-impact analysis and clustering, supported by the Davies–Bouldin index to validate the quality of clustering outputs [9, 19]. By aligning each scenario group with tailored strategic options, the model provides decision-makers with a structured yet flexible roadmap for responding to diverse

market conditions. This approach resonates with previous research emphasizing the value of scenario-based strategy development in volatile markets [8, 21].

The study's integration of multilayer perceptron (MLP) neural networks into the competitor pricing prediction subsystem reinforces the growing evidence that deep learning methods can outperform traditional statistical approaches in forecasting complex, non-linear relationships inherent in competitive markets [6, 24]. The high predictive accuracy achieved here aligns with findings in related domains, such as health insurance premium estimation [18] and short-term claims forecasting [19], where ML models have demonstrated superior adaptability to multidimensional datasets. Moreover, the prescriptive AI layer operationalizes these predictions by generating actionable recommendations, thereby addressing a common limitation in predictive analytics where outputs often remain underutilized in actual decision-making [2, 5].

A key strength of the proposed model is its capacity to link predictive outputs with scenario-based insights, thus enabling Parsian Insurance to shift from a reactive stance to a proactive competitive posture. This capability is particularly critical in environments characterized by fluctuating inflation rates, shifting regulatory landscapes, and evolving customer preferences [10, 22]. Previous studies have shown that organizations capable of integrating foresight into operational decision-making exhibit greater resilience and sustained competitive advantage [1, 17]. The current model builds on this understanding by embedding scenario evaluation metrics—Total Synergetic Impact, Descriptor Inconsistency Index, and Scenario Inconsistency Index—into its decision framework, ensuring that strategic recommendations are not only data-driven but also internally consistent with probable market futures [11, 12].

The clustering approach adopted in this study addresses a methodological challenge in scenario analysis involving qualitative variables. By selecting the K-modes algorithm—designed for categorical data—and validating results through the Davies–Bouldin index, the model ensures meaningful and interpretable scenario groupings [12, 20]. This methodological choice aligns with recent recommendations in explainable AI research, where interpretability is emphasized alongside predictive accuracy [9, 13]. Furthermore, scenario-based segmentation facilitates differentiated strategic planning for each cluster, a practice that has been shown to enhance strategic agility and resource allocation in dynamic sectors [16, 21].

From a practical standpoint, the study's results underscore the transformative role of machine learning in the insurance sector's competitive intelligence systems. The integration of internal financial data, regulatory developments, and market signals into a unified analytical framework mirrors emerging global best practices in business analytics and decision sciences [5, 7]. This multi-source data integration not only enriches the predictive power of the model but also strengthens its ability to detect weak signals—subtle yet significant changes in competitor behavior or market structure—that may precede larger disruptions [4, 17].

The findings also highlight that strategic responses must be tailored to each scenario's underlying conditions. For instance, in stability and cautious growth scenarios, conservative market share targeting combined with service quality enhancement is most effective, whereas in high-inflation, aggressive competition scenarios, risk-based dynamic pricing and advanced cost optimization are imperative. This nuanced alignment between environmental conditions and strategic actions reflects the insights of prior research on competitive strategy formulation in insurance and financial services [3, 8, 16]. It also reinforces the importance of balancing short-term survival tactics with long-term capability building, as evidenced by studies on digital transformation and innovation in insurance [10, 26].

Moreover, the study's emphasis on explainability and transparency in predictive models addresses a critical adoption barrier in regulated industries. By ensuring that model outputs can be interpreted and justified, the framework reduces resistance from decision-makers and aligns with calls for ethical and accountable AI in business contexts [13, 15]. This is especially relevant in markets like Iran, where public trust and regulatory oversight are intertwined with competitive practices [22, 23]. The deliberate integration of explainable AI principles ensures that strategic recommendations are not only effective but also defensible in compliance and governance contexts.

In sum, the results confirm that the proposed model delivers on its dual promise of predictive accuracy and strategic applicability. By embedding ML-based forecasting within a structured scenario planning framework, the model enables insurance firms to prepare for a wide range of plausible futures while maintaining flexibility in strategic execution. This integrated approach reflects an evolution in competitive intelligence from fragmented, retrospective analysis toward a cohesive, forward-looking capability [2, 5, 17]. The study thus contributes to the literature by offering a replicable methodology for other competitive and regulated sectors seeking to leverage AI for strategic foresight.

Despite its contributions, the study has several limitations. First, the model's predictive performance relies heavily on the quality and granularity of historical pricing and market data. In contexts where data is incomplete, inconsistent, or delayed, predictive accuracy may decline. Second, while the K-modes clustering approach is well-suited for categorical scenario variables, it does not account for potential interactions between categorical and numerical data types, which may limit the richness of scenario segmentation. Third, the study focuses primarily on the Iranian insurance market, particularly Parsian Insurance Company, which may limit the generalizability of findings to other markets with different competitive structures, regulatory regimes, or levels of technological maturity. Finally, although explainable AI principles were incorporated, the interpretability of certain deep learning components—such as the MLP network—remains constrained by the complexity of neural architectures, which could pose challenges for stakeholders unfamiliar with advanced analytics.

Future studies could explore hybrid clustering techniques that integrate both categorical and numerical scenario variables to capture more nuanced patterns in market futures. Additionally, expanding the dataset to include real-time streaming data—such as competitor social media activity, news sentiment, and macroeconomic forecasts—could enhance the model's responsiveness to sudden market shifts. Cross-industry comparative studies would also be valuable, enabling researchers to assess the adaptability of this model to other highly competitive and regulated sectors, such as banking, telecommunications, or healthcare insurance. Moreover, incorporating reinforcement learning into the prescriptive analytics layer could allow the system to continuously refine strategic recommendations based on feedback from actual market outcomes, thereby improving decision quality over time.

Practitioners implementing this model should prioritize establishing robust data governance frameworks to ensure data quality, security, and compliance. Cross-functional collaboration between data scientists, strategic planners, and regulatory experts is critical to translating model outputs into actionable strategies that align with organizational goals and market realities. Firms should also invest in continuous capacity building, ensuring that decision-makers develop the skills needed to interpret and apply predictive insights effectively. Finally, scenario-based strategic planning should be embedded into the organization's regular decision-making processes, ensuring that proactive, data-driven strategies become part of the corporate culture rather than isolated analytical exercises.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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