EUROASIA
Matematik, Mühendislik, Doğa ve Tıp Bilimleri Dergisi
Journal of Mathematics, Engineering, Natural & Medical Science

Research Article e-ISSN: 2667-6702 https://doi.org/10.5281/zenodo.15821904

Integrating Decision-Making Quality with Decision Support Systems: A Machine Learning Approach Based on Behavioural Insights from Business Professionals

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Article Info

Received: 25.03.2025
Accepted: 25.04.2025

Keywords
Decision-making quality
Decision support systems
Machine learning
Behavioural ınsights

Abstract: Decision-making quality is essential for organizational success and individual satisfaction. However, assessing and predicting decision quality has often stayed at a theoretical level and has not been integrated into practical tools like decision support systems (DSS). This study aims to close that gap by developing an approach based on machine learning that combines behavioural factors influencing decision-making with explainable artificial intelligence (XAI) techniques. Data were collected from business professionals across various industries, focusing on individual, environmental, and organizational factors that shape their decision satisfaction and regret. The dataset was balanced using synthetic sampling to ensure strong model performance. An XGBoost model predicted whether individuals would make the same decision again under current conditions. The model's performance was validated with ROC curves, confusion matrices, and SHAP analysis to identify the key factors that influence the outcomes. The findings showed that variables such as perceived organizational fairness, external pressures, personal experience, and intuitive processes had a significant effect on decision quality. Including these behavioural insights into DSS frameworks can improve the accuracy and practical relevance of these systems. This study contributes to the link between behavioural science, machine learning, and decision support, providing new perspectives for managers and system developers.

1. Introduction

Decision-making is an important process that affects both organizational success and individual satisfaction. Traditionally, it was believed that decision-makers could make the best choices by using complete information and logical thinking (Simon, 1955). However, Bounded Rationality Theory, introduced by Simon (1955) and later expanded by Kahneman and Tversky (1979) through Prospect Theory, challenged this view. This theory emphasized the cognitive limits and mental shortcuts that influence human decisions in uncertain situations. These studies led to a shift in decision sciences, showing that emotions, perceptions, and outside factors significantly impact decision quality.

Behavioral economics and psychology have demonstrated that people often show consistent biases and inconsistencies (Thaler, 2000; Kahneman, 2011). Within organizations, decision-making becomes more complex due to personal values, company culture, and outside pressures (Eisenhardt & Zbaracki, 1992). Nutt (2008) observed that many managerial decisions either fail or do not yield the expected results. This often occurs because decision-makers ignore the behavioral and contextual factors that affect their choices.

Additionally, decision regret and satisfaction are important but frequently overlooked when evaluating decision quality. As Zeelenberg and Pieters (2007) noted, regret is not just a feeling we experience afterward; it acts as a helpful feedback tool that can guide future decisions. Understanding whether decision-makers would make the same choice again can offer valuable insight into the long-term quality and acceptance of their decisions.

Despite these behavioural insights, the incorporation of decision-making psychology into Decision Support Systems (DSS) and modern machine learning models has been limited (Shmueli & Koppius, 2011). Traditional DSS frameworks usually rely on structured, quantitative data and often lack the ability to account for behavioral details. Recent developments in Explainable Artificial Intelligence (XAI), particularly SHAP (SHapley Additive exPlanations) values, provide a potential solution by offering interpretable models that clarify the decision-making process (Lundberg & Lee, 2017).

In this context, our study aims to create a machine learning-based decision prediction model that includes behavioural factors from business professionals. Unlike previous research, which mainly focused on financial or operational data, this study stresses the importance of including cognitive, emotional, and social variables that affect decision satisfaction and regret. By doing this, we aim to improve DSS by integrating human factors into predictive analytics.

Additionally, the increasing demand for human-in-the-loop systems highlights the need for DSS that not only offer accurate recommendations but also fit users' behavioural tendencies and ethical concerns (Doshi-Velez & Kim, 2017). Therefore, this study seeks to fill a significant gap by proposing an explainable, behaviourally informed DSS framework that can assist decision-makers in complex organizational settings.

The rest of this paper is organized as follows: Section 2 describes the literature review Section 3 materials and methods. Section 4 presents the findings and discussions. Section 5 provides conclusions and suggestions for future research.

2. Literature Review

Researchers have looked into decision-making processes in different areas, showing the complicated relationship between logical analysis and behavioural influences (Simon, 1955; Kahneman & Tversky, 1979). The traditional economic perspective often assumes that decision-makers are entirely rational and try to maximize utility based on complete information (Thaler, 2000). However, Simon's (1955) concept of bounded rationality challenged this idea. He suggested that people often make satisfactory rather than optimal choices due to cognitive limitations and environmental constraints.

Kahneman and Tversky’s (1979) Prospect Theory built on this idea. It showed that people perceive gains and losses differently, leading to behaviours that are either risk-averse or risk-seeking, depending on the context. In organizations, decision-making becomes more complex due to internal and external pressures, company culture, and the ever-changing business environment (Eisenhardt & Zbaracki, 1992; Nutt, 2008). Nutt (2008) argued that success in decision-making within organizations relies not only on rational evaluation but also on considering stakeholder opinions, dealing with time constraints, and trusting the decision-maker's intuition.

Behavioural decision-making in business is also shaped by cognitive biases, emotions, and social norms (Loewenstein et al., 2001). Emotions like regret and satisfaction not only result from decisions but also influence future choices (Zeelenberg & Pieters, 2007). Anticipated regret has emerged as a key factor in complex decision-making environments (Josephs et al., 1992), often leading decision-makers to delay choices or select safer options.

Recently, there has been growing interest in combining decision-making studies with Machine Learning (ML) and Decision Support Systems (DSS). Shmueli and Koppius (2011) stressed the significance of predictive analytics in information systems research, paving the way for linking data-driven models with behavioural insights. Algorithms like XGBoost have shown better predictive performance in classification tasks. They offer valuable help for managerial decision-making processes (Chen & Guestrin, 2016). Explainable Artificial Intelligence (XAI) has become essential in this area. It ensures that complex ML models can be understood by business leaders and stakeholders (Lundberg & Lee, 2017). SHAP values particularly improve clarity regarding feature contributions. This is crucial for implementing data-driven decision-making frameworks in organizations (Molnar, 2019).

Moreover, decision-making in organizations is increasingly influenced by cultural, social, and psychological factors (Hofstede, 1984; March, 1994). Research shows that perceptions of fairness, social responsibility, and personal beliefs significantly affect decision satisfaction and the likelihood of making consistent decisions (Colquitt et al., 2001; Aguinis & Glavas, 2012). Despite the growing research, few studies have explained decision quality and regret through machine learning-based behavioural models in real business settings. This study seeks to address this gap by using a data-driven approach that combines SHAP-based explainability, XGBoost classification, and a comprehensive set of behavioural and organizational variables to predict decision consistency among business professionals.
By achieving this, this research not only adds to the literature on behavioural decision-making but also connects managerial decision support systems with advanced machine learning techniques.

3. Materials and Methods

3.1. Research Design

This study uses a quantitative, explanatory research design to explore the factors that affect decision consistency among business professionals. The goal is to create a predictive model using machine learning techniques, specifically the XGBoost classifier, along with SHAP-based explainability to reveal the key drivers of decision-making behaviour.

3.2. Data Collection

The dataset came from a structured survey conducted with business professionals in different sectors, including manufacturing, services, and technology. Participants responded to questions about their recent strategic or operational decisions. The survey aimed to capture decision-specific factors like time pressure, risk perception, and alternatives considered, along with individual traits such as age, gender, experience, and personal beliefs.

We collected 201 valid responses. The data contained both categorical and numerical variables. It covered various influences on decision-making, including organizational dynamics, personal intuition, social pressures, and external environmental factors.

3.3. Variable Description

The target variable is "TodayAlsoDecision" I would make the same decision today, which measures whether participants would make the same decision again if they were in the same situation. This variable serves as a strong indicator of decision quality and consistency.

The independent variables include:

- Organizational Factors: Company size, industry type, job position, work-life duration.
- Personal Characteristics: Age, gender, educational background, experience.
- Behavioural Drivers: Regret experience, decision satisfaction, emotional influences, cognitive perceptions.
- Social and Cultural Factors: Beliefs, superstitions, perception of social expectations, and metaphysical considerations.

All variables were translated into English and prepared to ensure consistency and reliability.

3.4. Data Pre-processing

Missing values in numerical fields were filled in using the median.
Categorical variables were transformed into one-hot encoded format to make them suitable for machine learning algorithms.
SMOTE (Synthetic Minority Over-sampling Technique) was used to address class imbalance issues.

3.5. Model Development

An XGBoost classifier was chosen for its strength and high performance in multiclass classification tasks (Chen & Guestrin, 2016). The model was trained with these parameters:

- Learning rate: 0.1
- Maximum tree depth: 5
- Number of estimators: 150
- Evaluation metric: Multi-class log-loss

The dataset was divided into training (80%) and testing (20%) subsets using stratified sampling to maintain the class distribution.

3.6. Model Evaluation

The model's performance was evaluated using these metrics:

- Accuracy
- Precision
- Recall
- F1-Score

Additionally, Receiver Operating Characteristic (ROC) curves were created for each decision class to assess the model's ability to distinguish between classes.

3.7. Explainability with SHAP

SHAP (SHapley Additive exPlanations) values helped interpret the model outputs and show the contributions of features for each predicted class (Lundberg & Lee, 2017). This method increases the clarity of machine learning models and supports recent progress in Explainable Artificial Intelligence (XAI).The SHAP analysis helped identify the most influential factors behind consistent decision-making, providing valuable insights for developing decision support systems aimed at business professionals.

4. Findings and Discussions

The XGBoost classifier, which has proven effective in handling complex, non-linear relationships (Chen & Guestrin, 2016), was used to classify the responses based on behavioural and demographic variables. The model was backed by SHAP (SHapley Additive exPlanations) to provide clarity and transparency (Lundberg & Lee, 2017).

4.1 Descriptive Findings

The dataset used in this study includes responses from 201 business professionals. The participants shared their views on decision-making processes, influencing factors, and the quality of their decisions. Variable list at the end of the paper provides detailed variable descriptions and their English translations.
The distribution of the dependent variable, which measures the likelihood of making the same decision again under current circumstances (TodayAlsoDecision), shows a variety of perceptions about decision satisfaction among the respondents. This variation highlights the complexity and multiple aspects of decision-making in real-world business situations.

4.2 Model Performance and ROC Curve Results

The XGBoost classifier was trained with the balanced dataset created using the SMOTE technique to deal with class imbalance. The model reached an overall accuracy of 79% on the test set. It also achieved a macro F1-score of 79%, which shows a good ability to generalize. Detailed performance metrics are shown in Table 1.

Table 1. Model Performance Results for XGBoost Classifier

Class	Precision	Recall	F1-Score	Support
0	0.93	0.78	0.85	18
1	0.80	0.94	0.86	17
2	0.94	0.89	0.91	18
3	0.71	0.56	0.62	18
4	0.61	0.78	0.68	18
Overall Accuracy			**0.79**	89
Macro Average	0.80	0.79	0.79	
Weighted Average	0.80	0.79	0.79	

Multiclass ROC curves were created to assess the model's ability to classify different decision classes. The ROC analysis showed that the model does a decent job of distinguishing between different levels of decision quality, particularly for the classes that indicate high and low decision satisfaction.

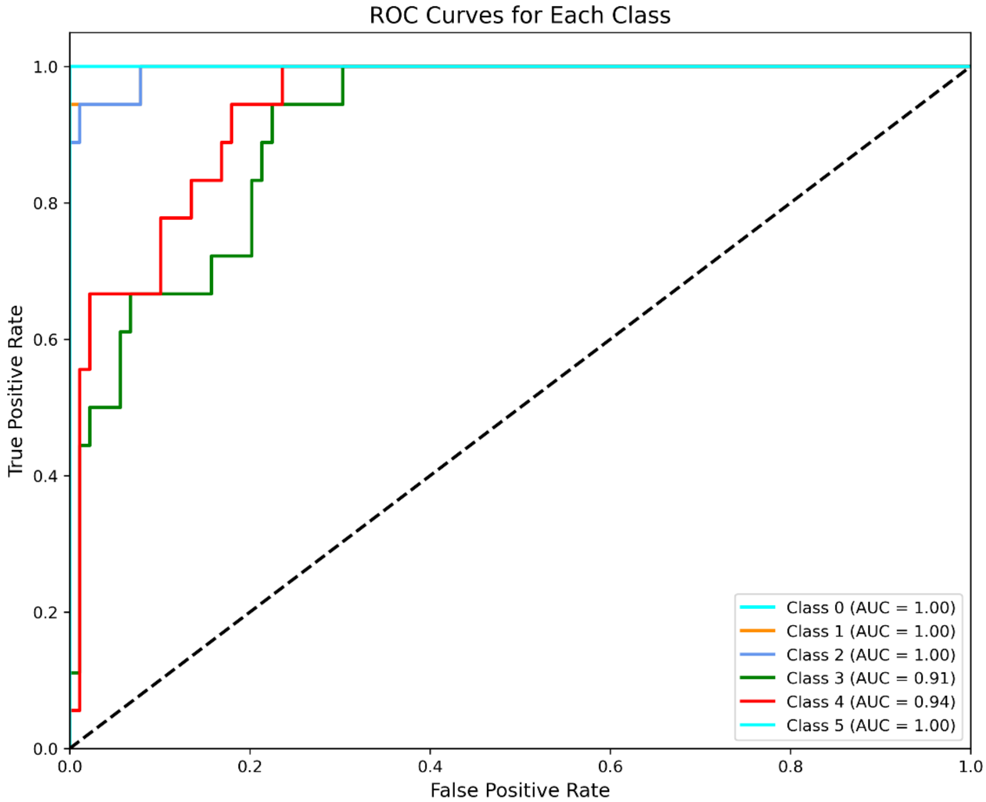


Figure 1. ROC curves.

The ROC analysis shows that the model can make reliable predictions. This is important for possibly integrating it into decision support systems in organizations.

4.3 Explainability with SHAP Values

The SHAP analysis helped to understand the model's predictions and pinpoint the most important features affecting decision-making quality. The SHAP summary plot showed that variables like Decision Satisfaction, Risk Decision, Rewards Decision, and Consulted Decision had the greatest influence on predicting if a decision would be repeated under current conditions.

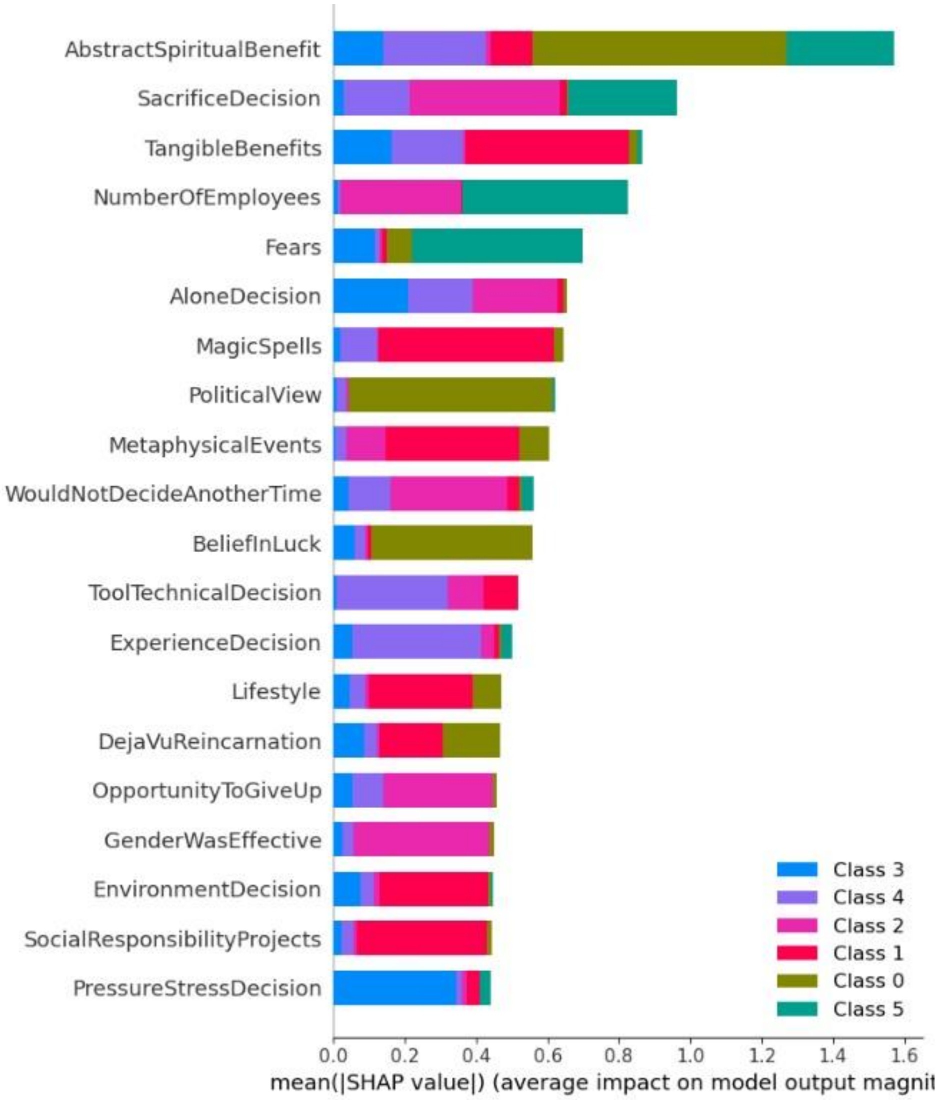
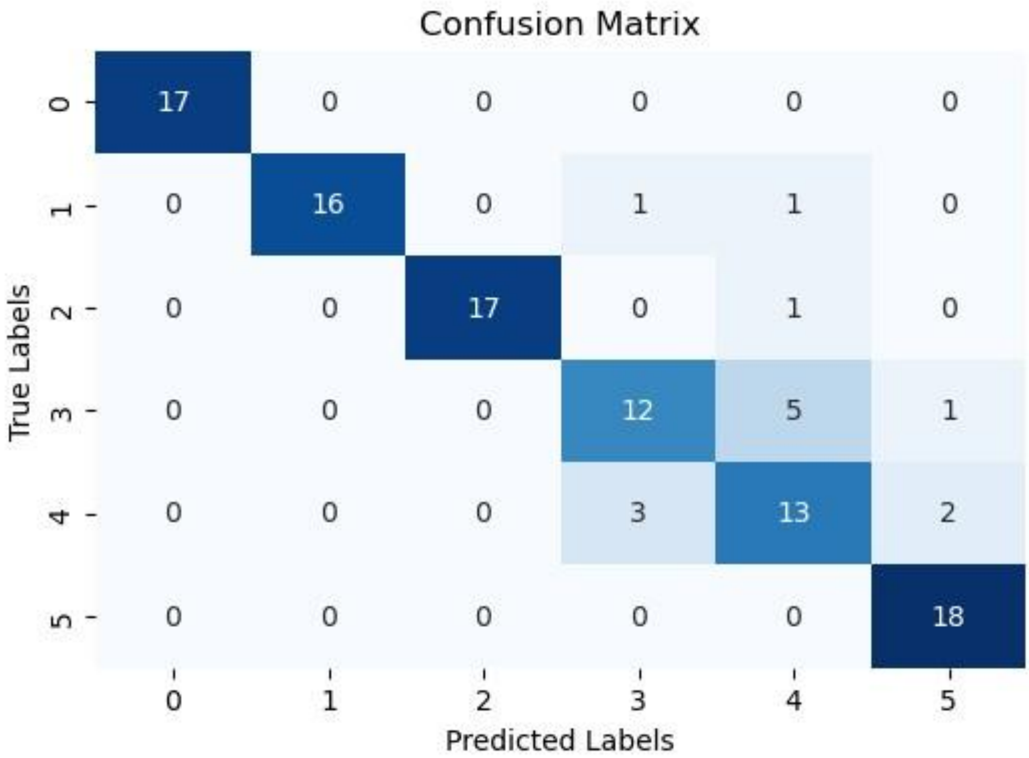


Figure 2. SHAP feature importance visualization

This finding agrees with the research on how people make decisions. It highlights the importance of emotional satisfaction, evaluating risk, and seeking social advice in making good decisions (Kahneman & Tversky, 1979; Nutt, 2008; Eisenhardt & Zbaracki, 1992).

In addition, factors like personal beliefs, cognitive biases, and outside pressures also showed up as important influences. This means that both logical and emotional factors affect how business professionals perceive decisions. This insight stresses the need to include behavioural aspects in decision support systems to improve their usefulness.

Table 2. Confusion Matrix



The confusion matrix of the XGBoost model is shown in Table 2. It summarizes the model's predictive performance across all classes. The diagonal elements represent the number of correctly classified instances for each class. The off-diagonal elements show misclassifications. The matrix indicates that the model achieved high classification accuracy for Class 0 and Class 2. However, some misclassification patterns appeared between Class 3 and Class 4. This suggests that while the model performs reliably overall, certain decision boundaries between specific classes may overlap. This could be due to similarities in decision patterns among business professionals. The confusion matrix not only supports the SHAP-based variable importance analysis but also serves as an important tool for evaluating class-specific precision and recall. Such detailed performance visualization is crucial for decision support systems. It helps ensure reliable predictions when applied in real-world management situations (Fawcett, 2006).

4.4 Discussion

The results from the machine learning model, especially with the XGBoost algorithm, showed strong predictive accuracy in assessing decision-making quality among business professionals. The SHAP analysis highlighted that both internal cognitive factors, like "Voice of My Mind" and "Knowledge and Skills," and external social influences, including "Voice of Society" and "External Factors," played a significant role in predicting decision consistency. These findings support earlier studies that stress the limitations of rationality in decision-making. Decisions are not just the outcome of logical reasoning; they are also influenced by emotions, social pressures, and contextual factors (Kahneman & Tversky, 1979; Nutt, 2008). Additionally, the varied contributions of factors shown in different SHAP summary plots indicate that decision quality is complex and needs analysis that goes beyond traditional models. The confusion matrix results showed that while the model works well across most classes, there are still minor misclassifications, especially in classes with subtle behavioural differences. This issue was also noted by Lundberg and Lee (2017) in complex predictive settings. These results highlight the importance of integrating machine learning-driven decision support systems into organizational processes. This integration can help capture the subtle, behaviour-driven patterns that conventional decision-making frameworks may miss.

5. Conclusion and Suggestions

This study combines decision-making quality assessment with machine learning-based decision support systems (DSS), using insights from business professionals. The findings show that decision quality is not only based on rational analysis; it is also greatly influenced by emotional, social, cognitive, and contextual factors. In particular, variables like "Voice of My Mind," "External Factors," and "Knowledge and Skills" stand out as key predictors, emphasizing the relationship between individual thinking and the organizational environment.

The strong performance of the XGBoost algorithm, confirmed by SHAP explainability analysis and ROC curve evaluations, shows that advanced machine learning methods are effective for modelling complex human decision behaviours. Moreover, the balanced precision and recall rates across various decision classes support the model's reliability and its potential use in practical DSS applications.

For future research, it is suggested to look into ensemble learning techniques or deep learning models to possibly uncover deeper patterns in decision-making data. Adding participants from different sectors and cultures would also help improve the findings' general applicability. Organizations should think about creating interactive DSS platforms that provide not only predictive outputs but also real-time feedback using explainable artificial intelligence (XAI) techniques to effectively support managerial decision-making.

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