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Detecting spatial and temporal myopia using machine learning algorithms

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Abstract

This study aims to examine the ability of machine learning algorithms to detect strategic myopia in organizations. As it consists of two variables, the first machine learning algorithms as independent variable with two dimensions: Decision trees classification and K- Means clustering, while the second variable is strategic myopia as dependent variable with two dimensions: spatial and temporal myopia. This study adopted a quantitative approach, and a publicly available HR dataset obtained from Kaggle was used to ensure data privacy. The dataset, which has been used in this study, represents the organizational internal factors with 14,999 employees' records. Both decision trees and K-means were applied to the internal factors' datasets, showing the likelihood of employees staying in the organizations and clustering the customers into three clusters. The study revealed that both decision trees and k-means can help organizations in detecting spatial and temporal myopia, and the researchers recommended that organizations should integrate machine learning algorithms in their decision-making processes.

Keywords: Strategic myopia, Machine learning, K-means, Decision tree

1. Introduction

One of the main competitive challenges facing organizations is ensuring long-term survival and success. Research [1] provided a new concept that most people were using this topic in the medical sector, which is myopia. Myopia, as a word, means the disability for someone to see distant objects. The same definition could be adopted when managers focus only on a single market or a single and narrow period. And in the business context, Levitt introduced it as marketing myopia by discussing four myths that lead managers to make poor decisions, which lead the organization to fail in their long-term success.

Organizations rely on strategic intelligence at all stages of the strategic management process, from internal and external environmental scanning to controlling their strategies. Gathering information of all kinds is crucial for

achieving this intelligence, which helps the organization make informed decisions. According to [2], business intelligence is closely related to setting up the organizational objectives and drawing the way to achieve them as strategic goals. Research shown in [3], scanning and observing the organization's internal and external environment is essential to predict the organization's future using historical data.

Any organization that focuses only on its current market and doesn't have any intentions to expand its scale will face challenges that could lead it to business failures at all due to its outdated processes and products [4]. Mining data using machine learning algorithms represents an important tool to detect both spatial and temporal myopia. By uncovering decision-making patterns and highlighting long-term trends across various organizational functions, data-driven insights enable managers at all levels to broaden their outlook, anticipate upcoming challenges, and make more well-rounded strategic choices, ultimately reducing short-term and narrow-minded thinking.

This study aimed to detect both strategic spatial and temporal myopia organizational decisions that could happen inside the organization while dealing with its employees' satisfaction and how it could affect their intentions to stay or leave the organization.

Strategic myopia, in which organizations only focus on immediate and short-term results and successes while ignoring the larger, long-term results and successes, still plagues many organizations. Organizations that make decisions based on this narrow-minded viewpoint are less able to compete with their rivals, are less able to adapt to their internal and external environments, and frequently waste or misallocate critical internal resources.

However, it takes a lot of work to make wise selections. It necessitates reading the organizational environment carefully, analyzing the information that is available both inside and outside the organization, and having a solid grasp of the facts being evaluated [5]. Many businesses use committees, working groups, or teams to make decisions. These cooperative agreements have many advantages, including utilizing a variety of knowledge, offering a broader range of potential solutions, boosting the acceptability of the final choice, and encouraging a better willingness among members to carry out the agreed-upon actions [6].

The dangers of strategic myopia are increased in a time of rapid technical advancement and frequent world upheavals. Organizations may react too slowly or insufficiently to new possibilities and risks when they prioritize short-term results while focusing on a small number of environmental actors, trends, or indicators [7]. The necessity for analytical tools that can identify and correct strategic myopia before it affects organizational performance is highlighted by the combination of shortsighted thinking and low environmental awareness.

Even while the causes and consequences of strategic myopia have been covered in detail in recent literature, most of the study is still conceptual. There aren't many studies that use data-driven or experimental methods to consistently find early signs of strategic myopia. Prior research has tended to concentrate on concept definitions, behavioral explanations, or qualitative insights, leaving a glaring methodological gap in identifying temporal and spatial myopia within real organizational data and identifying a simple tool that managers without technical expertise can use.

Traditional decision-making models are unable to detect subtle patterns or behavioral cues that suggest strategic myopia, especially within large and complex datasets. Machine learning algorithms offer a promising alternative tool, as they can uncover subtle relationships, cluster similar behavioral trends, and predict conditions associated with short-term decision bias. However, only limited experimental work has investigated how to apply machine learning algorithms, specifically decision trees and k-means clustering, to identify temporal and spatial forms of myopia in organizational contexts. This represents a gap that the current study seeks to fill. In response, this study proposes and evaluates a machine learning algorithm designed to identify strategic, temporal, and spatial.

By applying decision tree classification and k-means clustering, the research aims to provide a practical, data-driven tool to help managers detect early signs of strategic myopia decision-making behaviors and promote long-term strategic decisions. Despite the growing literature on strategic myopia, empirical and data-driven

approaches for detecting spatial and temporal myopia remain limited. This study addresses this gap by applying interpretable machine learning algorithms to real organizational data.

The main objective of this study is to examine the ability of machine learning algorithms to detect strategic myopia in organizations.

- Providing a conceptual framework for the study variables (machine learning and strategic myopia).
- Testing the ability of machine learning algorithms (decision tree and K-means) on detecting spatial myopia.
- Examining the ability of machine learning algorithms (decision tree and K-means) in detecting temporal myopia.

The importance of this study lies in its contribution to understanding key organizational variables that influence long-term sustainability, strategic decision-making, and future academic research.

- The variables examined in this study hold substantial importance for business organizations, as they play a vital role in ensuring their long-term survival and sustainable growth.
- The findings of this study will support top management in identifying ways to adopt a more long-term perspective in their decision-making.
- This study will provide future researchers with a solid foundation for further investigations, as no previous work has examined these two variables collectively or explored the relationships among them.

2. Study model

Figure 1 illustrates the proposed conceptual model of this study, which examines the impact of machine learning applications on mitigating or influencing strategic myopia. The model establishes a structural link between computational tools and organizational cognition through two primary dimensions. The conceptual model of this study consists of well-defined components that clarify the interaction between machine learning approaches and the dimensions of strategic myopia.

1) Independent variable (machine learning): This construct is operationalized through two distinct algorithmic approaches: Decision Tree (representing supervised learning) and K-Means (representing unsupervised clustering). These are utilized to process complex data environments that inform strategic choices.
2) Dependent variable (strategic myopia): To ensure a comprehensive analysis, strategic myopia is bifurcated into two critical dimensions:
   - Temporal myopia: The tendency of a firm to prioritize short-term gains over long-term sustainability.
   - Spatial myopia: The tendency to focus on local or familiar environments while overlooking broader, global, or peripheral market signals.

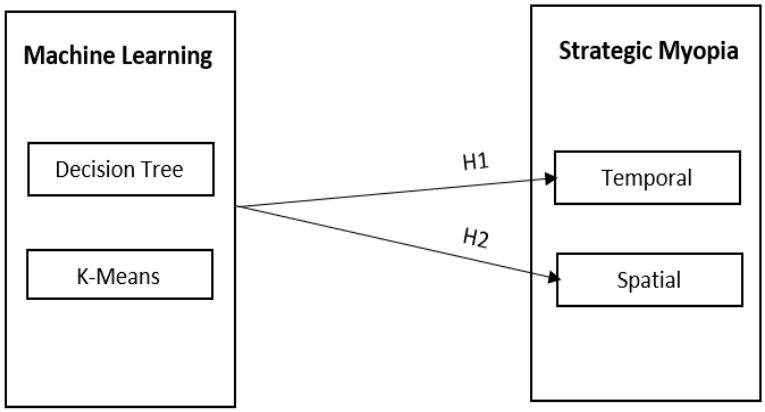

Figure 1. Research model

Drawing upon the conceptual framework, the study advances testable hypotheses to analyze the directional relationships between machine learning techniques and the temporal and spatial dimensions of strategic myopia. The model proposes two core pathways for analysis, represented by the directional arrows:

- Hypothesis 1 (H1): Postulates that the deployment of machine learning algorithms significantly affects the temporal dimension of strategic myopia.
- Hypothesis 2 (H2): Postulates a significant relationship between these analytical tools and the spatial awareness of the organization's strategic vision.

3. Theoretical foundation and hypothesis development

3.1. Strategic myopia

Strategic thinking is considered vital for organizations that aim to improve their competitive edge and maximize their market share. According to [8], this concept confirms the organization's need for ongoing enhancement even if this enhancement happens gradually, frequently propelled by originality and innovative ideas, and helps in formulating a future vision prior to undertaking the methodical, step-by-step processes of strategic planning. Long-term thinking supports this viewpoint by prompting decision-makers to avoid focusing on the short-term results and negative reflection on future consequences. In this framework, long-term strategy entails creating a detailed plan to address coming requirements, usually by projecting from existing or expected situations, which begins with evaluating the current scenario and illustrating a route towards the desired future [9]. Although it is widely acknowledged as significant, the theoretical definition and fundamental aspects of strategic thinking are still contested in scholarly discussions [10].

Businesses with strategic myopia prioritize short-term financial gain over long-term, sustainable objectives. Myopia is a medical term used to describe a person's inability to properly distinguish distant objects [11]. In terms of organizations, it denotes businesses that lack a long-term outlook and are unduly focused on achieving short-term goals. Three primary types of organizational myopia are identified by Levinthal and March: prioritizing short-term financial gain above long-term goals, disregarding more significant organizational or environmental factors, and failing to use lessons learned from past events to inform future decisions. Tackling this lack of foresight necessitates ongoing learning within the organization, which includes the acquisition of new information and the enhancement of current abilities, mindsets, and actions to foster effective long-term strategy.

Managers are required to make informed decisions by actions that harmonize immediate and future interests in line with real business circumstances; this task is deemed crucial for the long-term success of the organization. Nevertheless, agency issues frequently hinder managers from synchronizing these interests with the overall worth of the company, causing them to emphasize personal ambitions instead. Such a disparity often leads to an overemphasis on immediate results, a situation referred to as temporal myopia [12].

Temporal myopia means that an organization's struggle to balance decisions over various time frames, revealing a type of short-sightedness regarding time. In other words, temporal myopia means the organization focuses on achieving short-term and limited-term goals in a matter of time. For instance, a business might encounter a decision between maintaining short-term efforts that produce quick profits or committing to long-term projects that could lessen immediate gains but ultimately enhance the company's future standing [13]. This inclination can impede enduring growth and restrict the organization's strategic adaptability as time progresses.

Spatial myopia refers to a business's inability to effectively perceive and react to outside market circumstances, including trends within the sector that the organization works in, actions of rivals, and larger macro-environmental influences. This constrained perspective may lead to misaligned strategic goals, inefficient use of resources, and decreased organizational efficacy. Businesses and organizations that suffer from spatial myopia often fail to gather or analyze important environmental data, which results in decisions that do not fairly reflect real market behaviors [14].

3.2. Machine learning

The idea of machine learning, first presented by [15], enables computer systems to learn new things and improve their capabilities without the need for explicit programming instructions. Mitchell [16] subsequently provided a useful definition, saying that a computer program can learn from experience E about a task T and a performance metric P if, after exposure to E, its effectiveness on T, as measured by P, improves. Practically speaking, machine learning uses computer methods to find important patterns in data and create prediction models that can address problems in the real world, as explained by [17].

Machine learning, a key component of artificial intelligence, has transformed company operations by enabling automation, improving process efficiency, and enabling top management to make decisions based on data insights. This field focuses on creating algorithms that empower computers to learn from data called training data, enabling them to make predictions or decisions while continuously improving performance through the autonomous discovery of patterns and insights by deciding to formulate new strategies. Organizations are increasingly using machine learning to boost their operational efficiency, enhance their customer experiences and even their employees' experiences, and inspire innovation capabilities, according to [18]. It is essential to recognize that the success of any machine learning approach relies on having access to high-quality, trustworthy datasets and selecting an algorithm that fits the specific field, as noted by [19] and the researchers processing the dataset that was used in this research, by assuring that there is no missing data and editing the data types used.

Supervised, unsupervised, semi-supervised, and reinforcement learning frameworks are the four general categories into which machine learning techniques fall. Decision trees and other supervised learning methods rely on labeled datasets with predefined input and output targets. These models are extensively employed in domains such as determining whether to play tennis in particular weather conditions. They produce mapping functions that can classify or forecast new data instances. On the other hand, unsupervised methods, such as k-means clustering, operate on unlabeled information and seek to identify underlying patterns, similarities, and organic groupings, such as arranging personnel into clusters.

According to [20], reinforcement learning is a unique method that uses reward systems to guide autonomous agents and is particularly relevant in fields like robotics and adaptive systems. And K-means is a popular unsupervised machine learning technique that divides a dataset into k distinct clusters by evaluating feature similarities. For instance, the researchers in this study divided the employees into three clusters according to their evaluation rate and degree of satisfaction. The method continuously allocates data points to the closest centroid during this process, which centers each cluster around a "centroid" (a central point). The centroids are then updated to reduce the disparities within the clusters. This approach is widely used to group customers, such as VIPs and mass consumers, perform market research to better understand the needs and desires of the clusters, and find patterns. It also helps companies uncover natural clusters and extract useful insights from large datasets.

Because of their clarity and ease of comprehension for managers without technical backgrounds, decision trees are crucial machine learning techniques that are widely employed in a variety of industries, including the banking sector. They work by dividing data into smaller groups according to the values of attributes, which makes the results clear and simple to understand [21].

One of the simplest machine learning methods to comprehend and evaluate is decision trees. They outline the many decision-making processes and potential results while taking probability, uncertainty, and resource availability into consideration. Because of this, they are useful instruments for aiding in decision-making when there is insufficient or no information available [22].

3.3. Machine learning and strategic myopia

Recent advances in technology have sped up the development and application of machine learning, enabling computer systems to learn from unprocessed data and improve their performance without just relying on pre-

established rules [23]. In AI-based decision-making systems used by businesses, machine learning has become an essential component that may either improve expert judgment or expedite processes [24]. Machine learning facilitates data-driven and forward-thinking decision-making processes by enabling firms to find insights that would otherwise stay elusive through the management of large amounts of data [25].

Machine learning algorithms, such as decision trees and k-means clustering, are a great way to spot market trends and predict future outcomes, reducing the dangers of temporal and spatial myopia. While spatial myopia happens when businesses fail to align with market goals because of insufficient monitoring resources, temporal myopia refers to an imbalance between short-term and long-term decision-making [13] and [14]. Machine learning helps managers overcome these biases by providing data-driven insights that improve organizational effectiveness and strategic alignment.

Machine learning is being used by companies in a variety of industries, including finance, retail, healthcare, and cybersecurity, to improve processes, analyze customer behavior, spot operational risks, and forecast demand more precisely. The capacity to convert raw data into useful insights improves customer happiness, reduces waste, increases decision-making efficiency, and creates a sustainable competitive advantage [18],[14].

Building on this theoretical foundation, the present study proposes the following two main hypotheses:

H1: Both machine learning algorithms (decision tree and K-means) can detect temporal myopia inside the organization.

H2: Both machine learning algorithms (decision tree and K-means) can detect spatial myopia inside the organization.

4. Methodology

The study employed a quantitative analytical approach, utilizing a public dataset from the Kaggle website called (Employee HR Dataset), containing data for 14,999 employees. The database included several attributes as follows:

1. Employee satisfaction: (scale from 1 to 10)
2. Employee Evaluation (scale from 0 to 10)
3. Number of projects handled by employee
4. Time spent in the organization in years
5. Employee churn: either stayed or left

Prior to analysis, the dataset was examined for missing values and inconsistencies. All variables were reviewed and prepared to ensure compatibility with the applied machine learning algorithms. The models were implemented using Orange Data Mining software with default parameter settings; K-means clustering to explore employee internal segmentation patterns; and decision tree classification to identify their willingness to leave or stay in the organization.

5. Results

5.1. Decision trees

The internal factors considered in the analysis included:

1. Satisfaction
2. Evaluation
3. Number of Projects
4. Time Spent in Company

Figure 2 shows a decision tree that provides a hierarchical view of the most influential factors affecting employee retention. In the visualization, red nodes indicate a tendency to stay, while blue nodes indicate a tendency to leave.

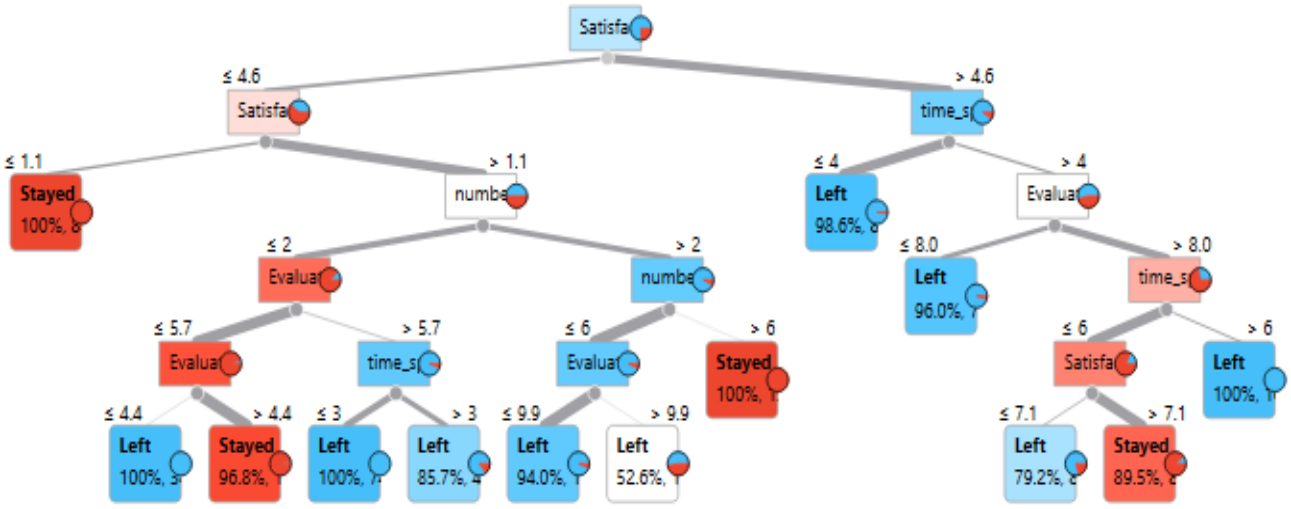

Figure 2. Decision tree model illustrating the impact of satisfaction, evaluation, number of projects, and tenure on employee churn

Key Findings

Satisfaction as the root node represented the most vital factor in predicting whether an employee stays or leaves the organization.

Low Satisfaction Path (Satisfaction ≤ 4.6)

- Employees with a low satisfaction rate (≤ 1.1) mostly stayed (100%).

Employees with low-to-medium satisfaction (>1.1 ≤ 4.6):

- The number of project employees worked has become the next most vital factor.
- Employees with ≤ 2 projects and Evaluation ≤ 4.4 had a 100% chance of leaving.
- Employees with ≤ 2 projects and Evaluation > 4.4 mostly stayed (96.8%).
- Employees with > 2 projects → Evaluation is the next split:
  - Evaluation ≤ 6 → 94% left
  - Evaluation > 6 → 52.6% stayed (mixed group)

High Satisfaction Path (Satisfaction > 4.6)

- Employees with short tenure (Time_S ≤ 4) exhibited a high likelihood of leaving (98.6%), indicating that early-career employees may exit rapidly despite high satisfaction.
- Employees with longer tenure (Time_S > 4):
- Evaluation becomes the next influential factor.
  - Evaluation ≤ 8 → 96% stayed
  - Evaluation > 8 → further splits on Time_S and Satisfaction:
    - Time_S > 6 → 100% left
    - Time_S ≤ 6 and Satisfaction ≤ 7.1 → 79.2% left
    - Time_S ≤ 6 and Satisfaction > 7.1 → 89.5% stayed

Interpretation

- Employees with low satisfaction rates, low evaluations, and few projects are at the highest risk of leaving.
- Even employees with high satisfaction may leave if their tenure is short or extremely long, highlighting the interplay between satisfaction, experience, and evaluation.

- The decision tree confirms that Satisfaction is the dominant predictor, but Evaluation and Tenure also significantly influence retention outcomes.

K-means

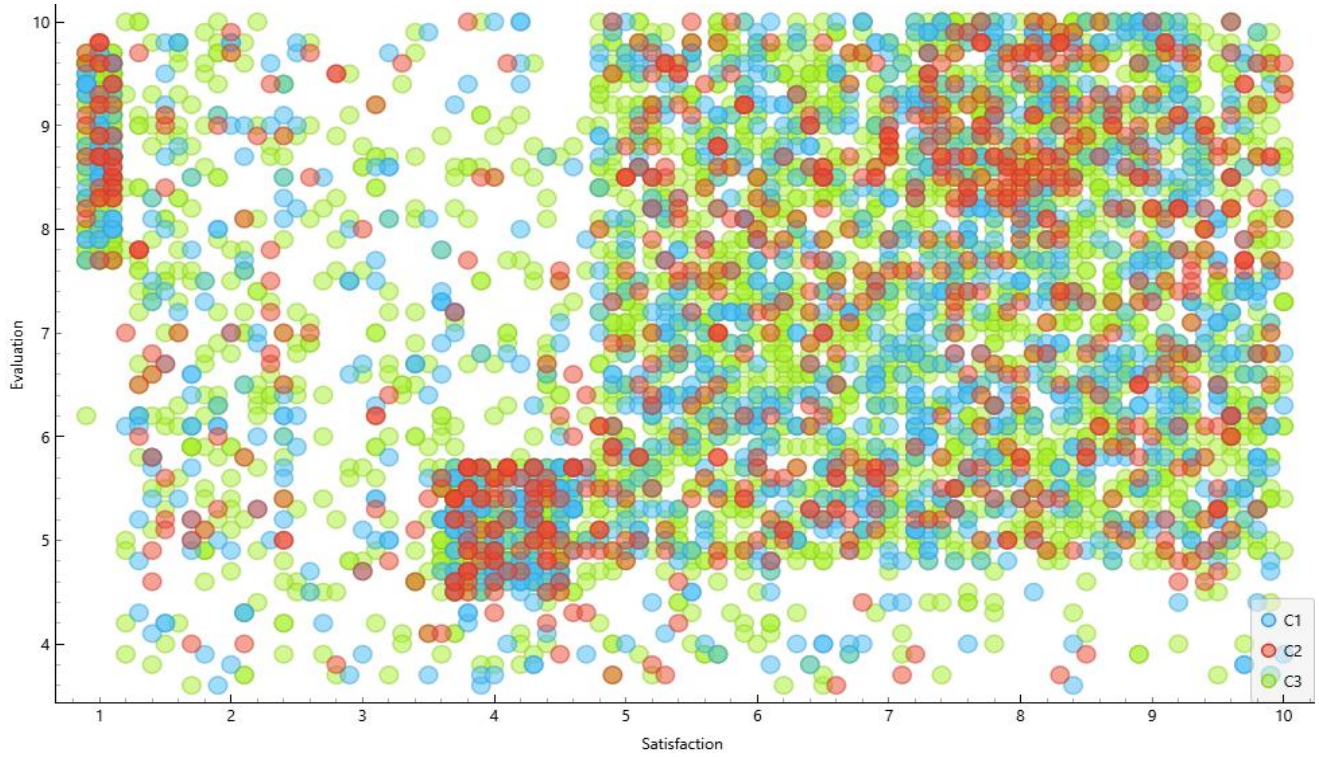

Figure 3. Scatter plot of employees grouped by K-means clusters based on satisfaction and evaluation. Cluster C1 (red) represents low satisfaction and performance, Cluster C2 (light blue) represents medium performers, and Cluster C3 (light green) represents high satisfaction and performance employees.

Figure 3 shows that K-means clustering analysis was applied to the same set of internal factors to identify natural groupings of employees based on their satisfaction, evaluation, and tenure. Three clusters (C1, C2, C3) were identified and analyzed, as discussed in Table 1.

Table 1. Cluster description

Cluster	Color	Characteristics	Likely Retention Status
C1	Red	Low satisfaction, low-to-medium evaluation, medium tenure	High risk of leaving or unstable
C2	Light Blue	Medium satisfaction, medium evaluation, some low tenure employees	Mixed risk; some new employees or moderate performers
C3	Light Green	High satisfaction, high evaluation, longer tenure	Likely to stay; stable and high-performing

Cluster Distribution and Insights

C1 (Red Cluster)

- Focused on low-to-medium satisfaction (4–5) and evaluation (4.5–5.5) regions, with some outliers in the high satisfaction/evaluation range.
- This cluster mostly represents employees who are dissatisfied or moderately evaluated, likely to leave or remain unstable in the company.

C2 (Light Blue Cluster)

- Shows a wider distribution, including some employees with very low satisfaction (=1) but good evaluations (7–10), likely new hires whose satisfaction scores have not stabilized.
- Also includes medium satisfaction and evaluation of employees, overlapping partially with C1.
- Represents a mixed-risk group, requiring attention for retention planning.

C3 (Light Green Cluster)

- Concentrated in high satisfaction (>5) and high evaluation (>7) areas.
- These employees are mostly stable, high-performing, and on average likely to stay in the organization.

Visualization and Interpretation

- The scatter plot below shows employees plotted by Satisfaction (X-axis) and Evaluation (Y-axis), colored by their cluster assignment.
- Interpretation:
  - C1 (Red): High risk of leaving; temporal myopia is evident as dissatisfaction and medium performance drive churn.
  - C2 (Light blue): Mixed cluster; some employees are new or moderately satisfied, representing potential turnover risk.
  - C3 (Green): Stable, high satisfaction and performance; represents spatially aware employees with longer tenure and strong retention likelihood.

6. Discussion

The results support H1, as both the decision tree and K-means analyses revealed patterns associated with short-term decision bias, indicating temporal myopia. H2 is also supported, as the clustering results highlight managerial focus on specific employee groups, reflecting spatial myopia.

6.1. Decision tree

The findings of the study indicated that employee satisfaction plays a vital role in shaping workers' decisions to stay with or leave an organization, a result that aligns with the conclusions of [26]. Consequently, organizations should prioritize initiatives that increase the satisfaction levels, as doing so can help lower the expenses associated with employee turnover. The decision tree analysis further emphasized the significance of this factor by placing it at the top of the model as the root node. The decision tree further revealed that employees with low satisfaction scores (less than 1.1) consistently choose to stay within the organization. This insight offers a strategic opportunity for management to focus on enhancing their satisfaction level and to explore the underlying causes behind their dissatisfaction.

The decision tree also indicated that employees who handle a limited number of projects (less than 2 projects) and receive low performance ratings are more likely to leave the organization even if they were satisfied, which may suggest that the organization should review its employee performance evaluation indicators because it could increase the stress on the employees and this stress will impact the employees productivity as this result agreed with [7]. Therefore, we can conclude from the above that employee satisfaction is very important in increasing employee commitment to implementing the organization's strategies, as their dissatisfaction means that the organization is concerned with quick results and not investing in them, and that it is focusing on increasing pressure on employees by not providing them with any support or rewards.

6.2. K-means

The findings of this study, as shown in Figure 3, indicate that employees were classified into three clusters (C1, C2, and C3). Employees in Cluster 1 (shown in red) have assessment ratings between 5 and 6 and satisfaction levels between 1 and 4. This implies that these workers are dissatisfied, which has a detrimental impact on their

performance reviews. Additionally, they are in their early years of employment, which may indicate that they are more likely to leave the company in pursuit of greater possibilities. Employees in Cluster 2 (shown in blue) have assessment ratings between 6 and 8 and satisfaction levels between 5 and 7. The performance and job satisfaction of these workers are mediocre. As a result, companies ought to encourage and assist them in raising their levels of assessment and contentment. Employees in Cluster 3 (shown in green) have high levels of appraisal and satisfaction. These workers show great dedication to the company.

Organizations should concentrate on improving employee satisfaction based on these clusters in order to increase long-term productivity as agreed upon, develop employee engagement, and promote the effective implementation of organizational plans [27]. Additionally, the clusters give top management clear indicators of the existence of disgruntled workers, emphasizing the necessity for the HR division to implement suitable retention strategies and concentrate on long-term planning rather than just current results and outcomes.

7. Conclusion

The aim of this study was to determine whether temporal and spatial myopia might be detected by machine learning methods. A publicly available dataset including employment data was taken from the Kaggle website. K-means was utilized to ascertain the number of employee clusters inside the company, and a decision tree was utilized to forecast whether an employee will remain or depart.

The results revealed several non-intuitive patterns after applying the machine learning algorithms using Orange Data Mining. Even if some workers were dissatisfied, they decided to remain with the company. On the other hand, several workers who had good evaluation ratings but ordinary satisfaction also made the decision to quit. Some employees with typical lengths of service and high levels of satisfaction left the company, according to the decision tree data.

This suggests that the decision tree assisted the company in identifying spatial myopia, which means that to guarantee staff retention, the company shouldn't concentrate only on three factors: time spent with the company, excellent assessment, and satisfaction. By showing where the company concentrates on immediate results and where high-rated people might have left because of work pressure, it also assisted in detecting temporal myopia.

Dividing employees into clusters using K-means revealed that the first cluster consisted of relatively new, low-satisfaction employees, indicating that the organization wasn't investing in their satisfaction and retention, and this considers temporal myopia. The third group, on the other hand, comprised highly satisfied employees with high evaluation ratings, demonstrating a spatial myopia because the organization was focusing on a single employee segment, prioritizing their satisfaction and retention.

8. Recommendations, limitations, and future work directions

Researchers recommend that organizations invest more in strategies to enhance their employees' satisfaction. As seen through algorithms, some employees, despite low satisfaction, choose to stay with the organization. This can be achieved by thoroughly investigating the reasons for dissatisfaction.

Furthermore, organizations should also consider the number of projects employees handle. An employee might be assigned numerous projects yet remain dissatisfied and still choose to stay. In these situations, companies ought to concentrate on creating fresh plans and determining if the worker has gotten the required direction and assistance. Additionally, it's critical to invest in new hires and capitalize on their enthusiasm as well as to identify and reward long-term, high-performing employees who are very satisfied.

This study has several limitations, despite the potentially useful findings that might give HR managers new avenues for investment, attention to long-term outcomes, and investigation of fresh approaches to employee retention. To safeguard the confidentiality of actual organizational data, it depended on a publicly accessible online dataset. As a result, the findings are specific to the data that was used and cannot be applied to other HR

managers. To obtain insightful information, each human resources department should apply these algorithms and closely examine the outcomes. Additionally, just two algorithms—decision trees and K-means—were used in this study, although there are others that could be advantageous to all organizational divisions.

Finally, this study focused solely on internal customers and employees and did not examine external customers or other stakeholders. Future research can expand the scope of this work by using other algorithms, both supervised and unsupervised, and by employing other analytical tools such as the Python programming language and real data related directly to the organization. Furthermore, future research can explore the impact of machine learning algorithms by identifying variables not used in this study in other sectors, such as customer service, logistics, and supply chain, even if they are the same variables but applicable to other departments, or by examining external organizational factors rather than internal ones.

Declaration of competing interest

No potential conflicts of interest were reported by the author(s).

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Author contributions

The contribution to the paper is as follows: Conceptualization R.A; Methodology R.A; Software R.A and H.A; Validation D.A and R.S.M; Formal analysis R.A; Resources R.A and H.A; Writing- original draft preparation R.A and H.A; Writing-review and edition Y.A and R.S.M; Supervision R.A.

All authors have read and agreed to publish version of the manuscript.

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