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A conceptual model for performance management

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ABSTRACT

BACKGROUND AND OBJECTIVES: The roots of Performance Management can be traced to ancient civilizations; however, the industrial revolution marked a turning point in this field, introducing concepts such as systematic evaluation, management by objectives, and excellence models. In modern times, PM has evolved to emphasize process analysis, self-assessment, benchmarking, and workforce development as core components. Despite these advancements, there is still a notable gap in the availability of a comprehensive, visually intuitive, and step-by-step framework to guide managers in implementing a holistic PM system. This manuscript aims to address this gap by introducing a detailed, graphical, and systematic PM model that provides clear guidance for practitioners.

METHODS: This study reviews various performance and excellence models to propose a novel conceptual framework. The proposed model is evaluated using the Analytic Hierarchy Process, Data Envelopment Analysis, and the Technique for Order of Preference by Similarity to Ideal Solution.

FINDINGS: The study constructs a new PM system by integrating an organization's mission, vision, strategies, processes, and stakeholder perspectives into Key Performance Indicators. It involves collecting relevant data, applying a scoring mechanism, calculating departmental efficiency, and ranking organizations to establish a data-driven decision-making framework. A case study is presented to illustrate the model's application, revealing that while DEA assigned 100% efficiency to two distinct organizations, TOPSIS yielded scores of 94.67% and 46.86%, with different rankings. The reasons for these discrepancies are thoroughly examined and discussed.

CONCLUSION: This manuscript introduces a conceptual model for PM, structured around eight key steps. These steps include team formation, indicator development, Balanced Scorecard development, weight calculation, scoring system design, data collection, data analysis, and feedback and continuous improvement. The model classifies KPIs into three main categories: specialized KPIs that are derived from missions, visions, strategies, critical success factors, and core processes. Self-assessment KPIs, developed based on established excellence models, and customer survey KPIs, designed to capture external stakeholder feedback. AHP is employed to determine the weights of the KPIs and BSC aspects, ensuring a systematic and objective prioritization. DEA is utilized for efficiency calculations, while the TOPSIS method is applied to analyze the results and derive actionable managerial insights. To demonstrate the model's applicability, it is implemented in a hypothetical municipality using arbitrary data, showcasing its capability to provide a comprehensive and structured approach to performance management.

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INTRODUCTION

Performance Management (PM) has undergone significant evolution over centuries, transitioning from philosophical and ethical considerations to structured organizational frameworks (Pulakos *et al.*, 2019). PM can be traced back to ancient civilizations (Otley, 1999). Confucius (c. 5th century BCE) emphasized self-improvement and ethical leadership, stating, "The superior man is modest in his speech but exceeds in his actions" (Soothill, 1910). Similarly, Socrates, through Plato's *Apology* (c. 399 BCE), advocated for self-examination: "The unexamined life is not worth living" (Miller and Platter, 2012). These ideas laid the foundation for personal and professional development, which later influenced performance assessment principles (Swanson, 2022). Persian scholars, including Rumi, Saadi, and Hafez, during the Middle Ages, contributed to the discourse on leadership and personal excellence (Davari, 2018). These philosophical perspectives align with modern performance evaluation's ethical considerations (Astin, 2012). The Industrial Revolution marked a significant shift in PM (Jensen, 1993). Taylor (1911) introduced systematic assessment methods, advocating for efficiency and productivity. Building on Taylor's work, Drucker (2012) introduced Management by Objectives (MBO), emphasizing goal alignment between employees and organizations. The 20th century saw the emergence of structured excellence models (Lubinski and Benbow, 2000). These excellence models provided a framework for continuous organizational improvement (Lubinski and Benbow, 2000). These models align with Goethe's assertion: "Knowing is not enough; we must apply. Willing is not enough; we must do" (Von Goethe, 2024). In the 1990s, Kaplan and Norton (1992) developed the Balanced Scorecard (BSC), integrating financial and non-financial performance measures. Understanding core business processes and the involvement of people is crucial for organizations striving for excellence (Oakland, 2007). Process analysis, self-assessment, benchmarking, and people development are key drivers in achieving organizational excellence (Oakland, 2007). Organizations should formulate their process objectives based on time, cost, and quality, using concrete and measurable performance indicators (Scheer *et al.*, 2005). By leveraging benchmarking, process comparisons, and best practices, organizations can attain excellence (Pemberton *et al.*, 2001). Gartner Group refers to this approach as "corporate performance management," which integrates processes, methodologies, metrics, and technologies to create a link between corporate strategy, planning, implementation, and control (Scheer *et al.*, 2005). PM enhances organizational capabilities by improving individual and team performance (Armstrong, 2009). It also ensures that the needs and expectations of all stakeholders—including owners, management, employees, customers, suppliers, and the general public are met (Armstrong, 2009). Organizations must evaluate their performance to assess how well they have achieved their goals (Domínguez *et al.*, 2019). PM is the process of quantifying efficiency and effectiveness (Valmohammadi and Servati, 2011). Effectiveness can be achieved through PM, which provides a systematic approach to setting work priorities and executing tasks efficiently (Pulakos *et al.*, 2019). Various PM initiatives exist, including performance-based budgeting, MBO, planning, programming and budgeting, and pay-for-performance systems (Heinrich and Marschke, 2010). DeNisi and Sonesh (2011) defined PM as a set of tasks aimed at improving the performance of individuals or groups to enhance organizational effectiveness. PM evaluates organizational activities based on Key Performance Indicators (KPIs) (Domínguez *et al.*, 2019). KPIs represent a set of measures focusing on critical aspects of organizational performance essential for current and future success (Parmenter, 2015). Well-defined KPIs facilitate strategy execution, enhance operational efficiency, and drive productivity and profitability (Domínguez *et al.*, 2019). Badawy *et al.*, (2016) categorize performance measures into four types: Key Result Indicators (KRIs): Measure achieved results based on Critical Success Factors (CSFs). Result Indicators (RIs): Indicate what has been accomplished. Performance Indicators (PIs): Show what must be done. KPIs: Highlight actions that significantly enhance performance. Several frameworks have been developed for KPI assessment. Domínguez *et al.* (2019) presented a taxonomy for KPIs and emphasized that KPI frameworks define conceptual and technical settings but do not necessarily focus on KPI definitions. Organizational excellence models serve as frameworks to guide organizations in achieving superior performance and continuous improvement (Ubaid *et* *al.,* 2020). The Deming Prize was established in 1951 by the Union of Japanese Scientists and Engineers (JUSE) (Union of Japanese Scientists and Engineers, 2010). This model emphasizes statistical quality control and Total Quality Management (TQM), advocating for systematic problem-solving and continuous improvement (Kaynak, 2003). The Malcolm Baldrige National Quality Award (MBNQA), introduced in 1987 by the U.S. Department of Commerce, provides a framework for performance excellence based on seven criteria: leadership, strategy, customers, measurement and analysis, workforce, operations, and results (National Institute of Standards and Technology, 2010). The European Foundation for Quality Management (EFQM) excellence model was launched in 1991 by EFQM(European Foundation for Quality Management, 2019). The earlier version of this model was structured around nine criteria divided into enablers (leadership, strategy, people) and results (customer satisfaction, business outcomes), while the updated version considers three aspects: direction, execution, and results (European Foundation for Quality Management, 2019). The Canadian framework for business excellence was developed by Excellence Canada and focuses on six drivers: leadership, planning, customers, people, processes, and partnerships (Excellence Canada, 2018). Various studies have proposed different KPI classification methods. The Supply Chain Council (SCC) introduced the Supply Chain Operations Reference (SCOR) model (Supply Chain Council, 2008), which classifies KPIs into five categories: reliability (task performance as expected), responsiveness (speed of task execution), agility (ability to respond to external influences), cost (expense of performing a process), and asset management (efficient asset utilization). Multi-Criteria Decision-Making (MCDM) models play a pivotal role in enhancing PM by providing structured methodologies for evaluating alternatives based on multiple, often conflicting, criteria (Sahoo and Goswami, 2023). PM has evolved into a comprehensive framework that requires organizations to assess, measure, and improve both operational and strategic goals (Taticchi *et al.,* 2012). The increasing complexity of organizational dynamics necessitates advanced tools and methodologies for effective decision-making (Smith, 2014). MCDM models have emerged as indispensable tools in this regard, enabling organizations to evaluate performance across diverse criteria and prioritize actions for improvement (Hwang and Yoon, 1981; Saaty, 1980). These models provide a systematic approach to address the challenges of performance evaluation by integrating both quantitative and qualitative criteria (Kaya *et al.,* 2019). MCDM models are widely used tools that assist decision-makers in evaluating and selecting the best alternatives among several options, based on multiple conflicting criteria (Massam and Bryan, 1988). These models can be broadly categorized into two types: compensatory models and non-compensatory models (Hwang and Yoon, 1981). In compensatory models, a poor performance in one criterion can be compensated by good performance in another (Hwang and Yoon, 1981). In contrast, non-compensatory models do not allow such trade-offs (Hwang and Yoon, 1981). Various methods have been developed to determine these weights, each offering distinct advantages depending on the complexity of the decision-making environment. The Analytic Hierarchy Process (AHP) (Saaty, 1980) and its extension, the Analytic Network Process (ANP) (Saaty, 2004), utilize pairwise comparisons to derive weights based on expert judgments, making them particularly useful for structured decision-making. The entropy method (Shannon, 1948) objectively determines weights by analyzing the dispersion of data, reducing reliance on subjective inputs. Additionally, the additive normalization method (Fichtner, 1986) and the eigenvector method (Saaty, 1980) employ mathematical normalization techniques and eigenvector calculations, respectively, to ensure consistency in weight assignments. The logarithmic least squares method and its variant, the weighted logarithmic least squares method (Crawford and Williams, 1985), utilize logarithmic transformations to enhance computational stability in weight determination. Furthermore, logarithmic goal programming (Tamiz *et al.,* 1998) integrates goal-setting techniques into the logarithmic model to optimize weight assignments. More advanced techniques, such as fuzzy preference programming (Mikhailov, 2003), incorporate uncertainty and expert opinions to improve the reliability of weight estimation. The Delphi method (Dalkey and Helmer, 1963) is another widely used approach that refines weight assignments through iterative expert feedback. Additionally, the best-worst method

Table 1: Literature comparison by the study

Authors	Conceptual model	AHP	DEA	TOPSIS	EFQM	BSC
Fahimi et al., 2024	✓	✓		✓		
Fahimi and Amirabadi (2024)	✓	✓		✓	✓	
Zeydan and Çolpan (2009)			✓	✓		
Vukomanovic and Radujkovic (2013)		✓			✓	✓
Sehhat et al. (2015)		✓		✓		
Kumar et al. (2020)		✓		✓		
Aydin et al. (2012)		✓			✓	
This study	✓	✓	✓	✓	✓	✓

(Rezaei, 2015) enhances decision consistency by identifying the best and worst criteria through structured pairwise comparisons. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) ranks alternatives by considering both the distance from the ideal solution and the distance from the negative ideal solution (Hwang and Yoon, 1981). It assumes that the best alternative is the one that is closest to the ideal solution and farthest from the negative ideal solution (Hwang and Yoon, 1981). VIKOR (Vise Kriterijumska Optimizajica I Kompromisno Resenje) is particularly useful when a compromise solution is required (Opricovic and Tzeng, 2004). It aims to provide a solution that is closest to the ideal and reflects the decision-maker's preferences in terms of the compromise among conflicting criteria (Opricovic and Tzeng, 2004). The Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE) focuses on pairwise comparisons and ranks alternatives based on preference functions, making it suitable for decision situations where preferences are qualitative or subjective (Brans *et al.,* 1986). Among the various decision-making models, Data Envelopment Analysis (DEA) has emerged as a powerful non-parametric method used for assessing the relative efficiency of Decision-Making Units (DMUs), which can be organizations, departments, or projects (Cook and Seiford, 2009). DEA is particularly useful when evaluating the performance of organizations with multiple inputs and outputs, as it does not require any assumption about the functional form of the production process (Charnes *et al.,* 1978). DEA compares the efficiency of DMUs by constructing an empirical frontier based on the best performers in the dataset (Charnes *et al.,* 1978). Each DMU is compared to this frontier to determine its relative efficiency (Charnes *et al.,* 1978). Zeydan and Çolpan (2009) proposed a decision support system for performance measurement using a combined fuzzy TOPSIS/DEA approach. Wijaya and Wahyono (2022) implemented the TOPSIS method for an employee performance information system. Vukomanovic *et al.* (2007) developed an integrated PM model tailored for the construction industry, combining the principles of EFQM and BSC. Aydin *et al.* (2012) introduced a hybrid methodology integrating AHP and EFQM models to assess business performance excellence. Sehhat *et al.* (2015) designed an evaluation framework incorporating specific indicators to rank and weight criteria, applying AHP and TOPSIS to analyze seven insurance companies. Kumar *et al.* (2020) utilized a combined AHP-TOPSIS approach to prioritize critical factors for the successful implementation of agile manufacturing within the Indian manufacturing sector. More recently, Fahimi *et al.,* (2024) proposed a performance evaluation model for the Tehran Municipality, leveraging TOPSIS and AHP. Additionally, Fahimi and Amirabadi (2024) constructed an organizational excellence model using the same techniques. A comparative analysis of this study with the existing literature is presented in Table 1.

PM process typically involves several key steps: identifying the various dimensions of the organization, determining the relevant indicators for each dimension, assigning weights to these indicators, scoring organizational units based on these indicators, constructing a decision matrix, normalizing the data, selecting the most appropriate evaluation technique, ranking the departments, and developing targeted improvement plans based on the results. The assignment of indicator weights, which relies on utility functions and the preferences of decision-makers, plays a pivotal role in shaping the outcomes of performance evaluations. Therefore, this study aims to address the following questions: What constitutes an effective PM model? How can KPIs be defined, and appropriate weights be assigned to them? How can an organization be evaluated systematically using these defined criteria? To answer the questions, this study presents a conceptual model designed to guide organizations towards excellence, accompanied by a practical implementation roadmap. Its comprehensive nature makes it a versatile tool for continuous improvement. By implementing this model, organizations can more effectively align their strategies with performance outcomes, thereby enhancing decision-making processes. This ensures that PM transitions from a theoretical concept to a practical, actionable strategy for sustainable organizational growth. The study outlines an eight-step process for achieving total organizational excellence. These steps are as follows: PM team formation: The initial phase involves assembling a dedicated team of PM experts and domain specialists responsible for overseeing the implementation of the model. KPI development: The second step focuses on the development of KPIs, divided into five sections:

a) KPIs based on the organization's mission, vision, and strategic objectives.

b) KPIs linked to core processes that directly impact the organization's competitive advantage.

c) KPIs related to general processes that support overall operations.

d) Self-assessment questionnaires based on established excellence models, completed by employees to gauge internal perceptions of performance.

e) Customer-oriented questionnaires that capture external feedback on performance, ensuring a comprehensive 360-degree evaluation of the organization.

BSC development: This step involves mapping the defined KPIs into the BSC framework, ensuring alignment with strategic objectives and providing a structured perspective on performance. Weight determination: The fourth step focuses on determining the weight of each KPI, reflecting its relative importance to the organization's goals and strategic priorities. Scoring system design: This step involves developing a scoring system to evaluate the performance of each KPI, facilitating comparative analysis and performance tracking. Data collection: The sixth step entails the collection, cleaning, and storage of data, ensuring its accuracy and reliability for subsequent analysis. Data analysis: In this step, the rank of departments is calculated based on the obtained scores. Corrective actions: The final step involves implementing corrective actions based on the analysis to ensure continuous improvement and alignment with strategic goals. The current study was carried out in the offices of performance evaluation in planning, human capital development, and the council affairs department at Tehran Municipality in 2025.

MATERIALS AND METHODS

Survey design and data collection

PM is a critical framework that enables organizations to assess their alignment with strategic goals, monitor progress, identify deviations, and address stagnation. A PM system must provide comprehensive insights into the operational dynamics of the organization, facilitating the identification of key areas for improvement. The development of KPIs is central to this process. These indicators should be rooted in various foundational elements, including CSFs, core processes, customer survey results, benchmarking activities, and self-assessment outcomes. By leveraging these diverse data sources, organizations can gain valuable insights into potential bottlenecks and inefficiencies that may impede overall performance. A critical aspect of building an effective PM model is the accurate identification and articulation of core processes. These processes are central to the organization's operations, and their alignment with strategic goals is essential for achieving sustained success. If core processes are inadequately defined or misaligned with the organization's mission, the pursuit of organizational excellence becomes an elusive goal. A robust model ensures that these processes are mapped, managed, and optimized to drive performance at every organizational level. Self-assessment frameworks, such as the EFQM excellence model, are instrumental in guiding organizations through the process of identifying improvement opportunities. These frameworks offer a structured approach to evaluating organizational performance, often highlighting critical areas for development, such as workforce development, training needs,

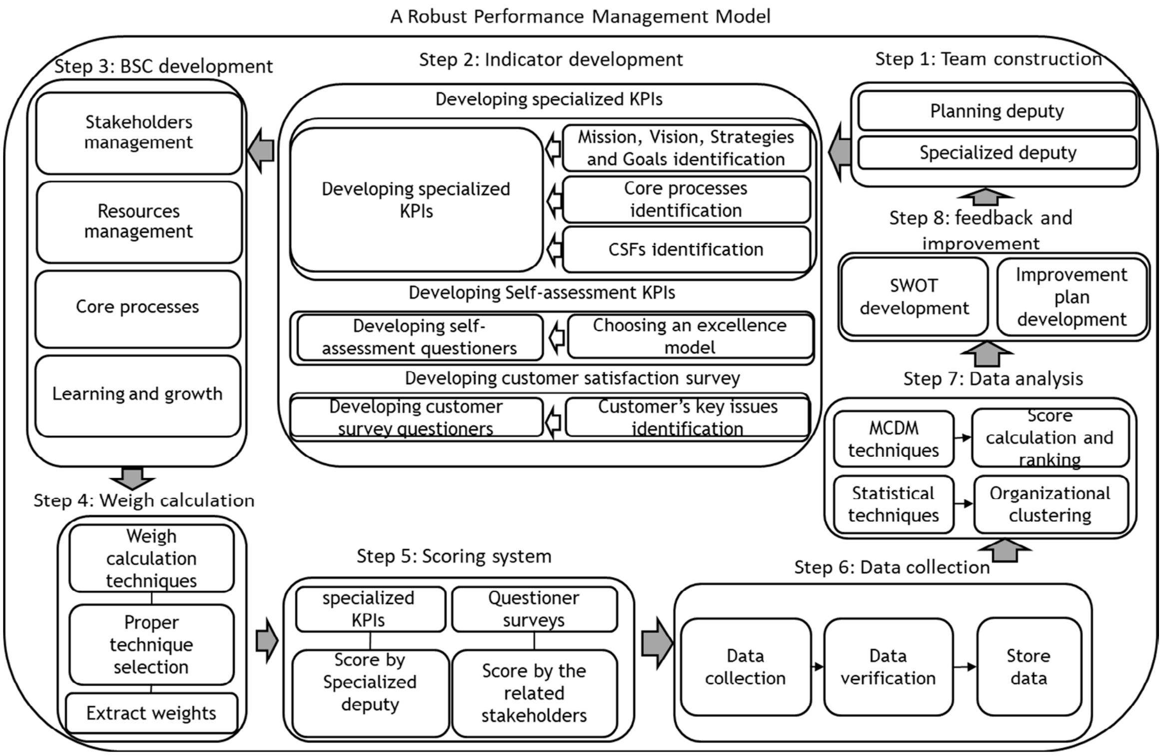

Fig. 1: A robust performance management model

and organizational culture. Addressing these areas is essential for fostering a culture of continuous improvement and aligning employees' capabilities with organizational goals. Additionally, customer surveys are indispensable tools in the pursuit of excellence. Customer feedback provides organizations with invaluable insights into customer expectations, perceptions, and satisfaction levels. This data serves as a foundation for aligning internal processes with customer needs, enabling organizations to adapt their strategies to enhance customer satisfaction and performance continually. The feedback mechanism embedded in this process ensures that organizations remain responsive to evolving market conditions and customer preferences. A truly robust PM model integrates these components—clear identification of core processes, self-assessment tools, customer feedback, and continuous improvement strategies—into a cohesive system that drives organizational performance. The proposed PM model is illustrated in Fig. 1, with its detailed components described as follows.

Step 1: Team formation

The initial phase of any PM project is centered around the formation of a specialized team. The importance of assembling a well-rounded, cross-functional team cannot be overstated, as it serves as the foundation for executing all subsequent stages of the project. The team should consist of PM experts with specialized knowledge in performance measurement and improvement, as well as domain specialists from within the organization who possess deep insights into specific operational areas. This interdisciplinary team is entrusted with the responsibility of developing and executing a PM system that aligns with the organization's strategic goals and objectives.

Step 2: Indicator development

After establishing the PM team, the next crucial phase is the development of performance indicators. A well-structured set of KPIs ensures that organizational objectives are measurable, actionable, and aligned with strategic goals. The systematic design of indicators allows organizations to track performance, identify inefficiencies, and implement continuous improvements. Performance indicators are broadly categorized into three main groups, each serving a distinct purpose in strategic performance evaluation. Mission-driven indicators are derived from an in-depth analysis of the organization's mission, vision, strategies, and objectives. They ensure alignment between organizational aspirations and measurable outcomes. Key elements include strategic KPIs, goal-specific metrics based on long-term business strategies, and vision-driven benchmarks that reflect future-oriented success measures. CSF-based indicators are developed based on CSFs, which are the key areas that determine organizational success (Rockart, 1979). Developing KPIs based on CSFs effectively ensures that key operational priorities are measured. Process-oriented indicators require a comprehensive understanding of core business processes for effective performance management. By mapping or flowcharting core processes, organizations gain a holistic view of operational activities, facilitating optimization and continuous improvement (Hammer and Champy, 1993). These indicators are designed for functional units and departments with unique objectives. Examples include financial KPIs, operational KPIs, and innovation KPIs. Key analytical questions to refine process indicators include: What are the organization's main products or services? Which key processes support these offerings? Who is responsible for each core process? What are the inputs, outputs, and impacts of these processes? How do these processes align with strategic goals? Additionally, self-assessment KPIs can be developed using established excellence frameworks, such as the EFQM model, which assesses organizational performance based on criteria such as leadership effectiveness, process efficiency, and customer engagement. Customer-centric KPIs should be developed based on key customer concerns and satisfaction drivers. One widely used framework is the Kano Model (Sauerwein *et al.,* 1996), which categorizes customer needs into basic needs (must-have attributes), performance needs (linear satisfaction metrics), and excitement needs (differentiation metrics). By integrating specialized indicators, self-assessment models, and customer survey data, organizations can establish a comprehensive KPI framework that provides actionable insights for strategic decision-making.

Step 3: BSC development

After identifying and defining KPIs, the next critical phase in the PM model is the development of a BSC. The BSC framework, as introduced by Kaplan and Norton (1992), traditionally consists of four primary perspectives, each of which plays a vital role in strategic performance assessment. However, in this adapted version, the financial perspective is replaced by resource management, and the customer perspective is replaced by stakeholder management. The primary reason for these replacements is to ensure that the developed BSC can be effectively applied to both profitable and non-profit organizations. By focusing on resource management, the framework emphasizes the efficient and sustainable use of resources, which is critical for all types of organizations. Similarly, replacing the customer perspective with stakeholder management broadens the scope to include all relevant stakeholders, making the model more inclusive and adaptable to diverse organizational contexts.

Step 4: Weight calculation

The subsequent phase entails determining the relative weights of the KPIs and aspects of BSC. To achieve this, AHP is employed to derive the weights of the criteria. For this purpose, a hierarchical structure of the indicators is constructed based on the BSC perspectives. Pairwise comparisons are then conducted both between the perspectives and among the indicators within each perspective to compute their respective weights. Consider a pairwise comparison matrix $=\left[a_{ij}\right]$ whe $i \text{ and } j=1,$ Here a_{ij} represents the preference value of the element i over element j. All entries in the matrix are positive $a_{ij}>0,$ and satisfy the reciprocal property, meaning $a_{ji}=\frac{1}{a_{ij}}$. The criteria defined at each level, along with the elements of the subsequent level, are compared pairwise using the 1–9 scale of pairwise comparisons, as illustrated in Table 2. The total number of pairwise comparisons required is given by the formula $\frac{n(n-1)}{2}$.

weight vector $(W_1,..,W_n)$ associated with the matrix A can be derived using the normalization of the geometric mean method. Let W_i denote the weight of the element i in matrix A. The geometric mean for

Table 2: The scale of pairwise comparisons

Degree of Importance	Definition	Explanation
1	Equal importance	Two criteria have equal importance according to the objective.
2	Weak or slight	According to the objective, the first criterion has weak or slight importance compared to the second criterion.
3	Moderate importance	The first criterion has moderate importance compared to the second criterion according to the objective.
4	Moderate plus	Between 3 and 5
5	Strong importance	The first criterion has strong importance compared to the second criterion according to the objective.
6	Strong plus	Between 5 and 7
7	Very strong	The first criterion has very strong importance compared to the second criterion according to the objective.
8	Very, very strong	The first criterion is very important to the second criterion according to the objective.
9	Extreme importance	The first criterion has extremely strong importance compared to the second criterion according to the objective.

$$W_i = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}}, \qquad i, j = 1, \ldots, n. \tag{1}$$

Each element i is calculated using Eq. 1.

To ensure the reliability and acceptability of the pairwise comparison matrix, a consistency check is performed. This step verifies that the evaluations made during the pairwise comparisons are logically consistent and free from contradictions. Let C be an n-dimensional column vector representing the sum of the weighted values for the importance degrees of the elements in the matrix A. This vector is defined as: $C = [c_i]_{n*1} = A.W^T,\ i = 1,\ldots,n$. Where W is the weight vector. The Consistency Value (CV) can be expressed as: $CV = [cv_i]_{1*n}$ where $cv_i = \frac{c_i}{w_i},\ \ i = 1,\ldots,n$. Using these values, the inconsistency index can be computed to assess the effectiveness and reliability of the pairwise comparisons. Saaty (1987) introduced the concept of the maximum eigenvalue (γ_{max}) to assess the consistency of pairwise comparison matrices. The maximum eigenvalue is calculated as: $\gamma_{max} = \frac{\sum_{i=1}^{n} cv_i}{n},\ i = 1,\ldots,n$. Where cv_i represents the consistency value for each element. Using γ_{max} The Consistency Index (CI) is determined as follows: $CI = \frac{\gamma_{max} - n}{n-1}$. Subsequently, the Consistency Ratio (CR) is defined as: $CR = \frac{CI}{RI}$. Where RI is the Random Index, which depends on the order of the pairwise comparison matrix. Table 3 provides the average values of RI for matrices of different orders. A CR A value below 0.1 indicates that the matrix is consistent, the evaluations are rational, and the derived weights are valid. If the CR exceeds 0.10, they should be reviewed and revised to improve consistency.

Step 5: Scoring system

At this stage, KPIs have been developed, and the BSC has been designed. The next crucial step involves collecting data (score) for each KPI, a responsibility assigned to the respective personnel overseeing its execution. Data related to specialized KPIs are gathered from the relevant specialized departments, ensuring accuracy and domain-specific insights. Meanwhile, self-assessment metrics and customer satisfaction data are primarily derived from structured questionnaires. To maintain the reliability and validity of the data, standardized methodologies should be employed in designing these questionnaires, ensuring they effectively capture performance-related insights. Furthermore, the scoring system should be designed to align with organizational strategic objectives, ensuring that KPI measurements reflect actual performance improvements.

Step 6: Data collection

The data collection phase is a critical step in the PM system, as it bridges the design of the scoring system with its practical application. This phase encompasses three primary components: data collection, data verification, and data storage. Data for performance evaluation is gathered from various sources, depending on the nature of the KPIs (Pyzdek and Keller, 2014). Quantitative data, such as financial metrics or operational statistics, are typically obtained from internal systems or automated processes.

Table 3: Consistency ratio

Matrix size	1	2	3	4	5	6	7	8	9	10
Random consistency	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Qualitative data, such as employee feedback or customer satisfaction surveys, may require tailored collection tools like structured interviews or questionnaires. To ensure comprehensive coverage, it is essential to identify and document the data sources in the earlier stages of the system design (Montgomery, 2017). Once collected, data must be verified to ensure its accuracy, reliability, and relevance. Verification processes may include cross-referencing with existing records, employing statistical methods to identify anomalies, or conducting manual reviews for sensitive qualitative inputs. Ensuring data integrity at this stage minimizes errors that could undermine the credibility of the scoring system and subsequent decision-making processes (Kaplan and Norton ,1992). Proper storage of verified data is critical for long-term analysis and traceability. Data should be stored in centralized databases with secure access controls to prevent unauthorized manipulation or loss (Pyzdek and Keller, 2014).

Step 7: Data analysis

This part used a basic model of DEA to evaluate departments or different organizations with different input structures, operational capacities, and resource availabilities. The mathematical formulation of the model is as follows (Charnes *et al.,* 1978):

$$\text{Max } Z_o = \sum_{r=1}^{s} u_r y_{ro} \tag{2}$$

$$s.t$$

$$\sum_{i=1}^{m} v_i x_{io} = 1 \tag{3}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \tag{4}$$

$$v_i, u_r \geq 0 \tag{5}$$

where:

Z_o represents the efficiency score of the DMU under evaluation (o).

j , o represent set of DMUs ($j = 1 \cdots n$, $\forall o = 1 \cdots n$)

i represent set of inputs ($\forall i = 1 \cdots m$)

r represent set of outputs ($\forall r = 1 \cdots s$)

x_{ij} and y_{rj} are the inputs and outputs, respectively, for each DMU.

u_r are the weight outputs.

v_i are the weight inputs.

The objective is to find the efficiency score of the target DMU o (Eq. 2). Eq. 3 is the input constraint (efficiency condition). This constraint normalizes the weighted sum of inputs for DMU o to 1, ensuring the efficiency score is bounded between 0 and 1. Eq. 4 ensures that the efficiency score of every DMU (including DMU o) does not exceed 1. Eq. 5 ensures that the weights assigned to peer DMUs are non-negative.

Step 8: Feedback and continuous improvement

A robust feedback mechanism and an effective continuous improvement strategy are crucial for ensuring the sustainability and effectiveness of a PM system. Following the application of quantitative performance analyses, such as DEA, organizations must implement structured feedback loops to enhance decision-making and drive long-term improvements (Montgomery, 2017). Organizational processes can generally be classified into three key categories, each requiring a distinct approach to optimization (Hammer and Champy, 1993). The first category includes processes requiring continuous improvement. These processes exhibit stable performance but benefit from incremental refinements through real-time monitoring and iterative enhancements. Continuous improvement frameworks, such as the PDCA (Plan-Do-Check-Act) cycle (Montgomery, 2017), lean management (Pyzdek and Keller, 2014), and Statistical Process Control (SPC) (Montgomery, 2017), can be utilized to minimize inefficiencies and enhance operational consistency. The second category pertains to processes in need of re-engineering or redesign. When efficiency and effectiveness fall significantly below expectations, fundamental modifications are required. This approach involves Business Process Reengineering (BPR), a radical redesign of workflows to achieve dramatic improvements in productivity and quality (Hammer and Champy, 1993), as well as process optimization through Machine Learning (ML) and Artificial Intelligence (AI), where predictive analytics can identify bottlenecks and recommend optimized resource allocation (Kaplan and Norton, 1992). The third category involves processes demanding strategic transformation. For processes that no longer align with organizational goals or market dynamics, a comprehensive reassessment of the business model is necessary. This may include strategic foresight and scenario analysis (Kaplan and Norton, 1992), digital transformation to leverage technology for enhanced efficiency, and sustainability integration to align with environmental and social governance principles (Pyzdek and Keller, 2014). A structured approach for evaluating organizational feedback and identifying areas for improvement is SWOT analysis (Strengths, Weaknesses, Opportunities, and Threats). It provides a strategic framework for categorizing internal and external factors affecting performance (Kaplan and Norton, 1992). By leveraging SWOT analysis, organizations can develop targeted improvement strategies that align internal capabilities with external opportunities while mitigating risks. To ensure that feedback leads to measurable improvements, organizations should implement structured feedback mechanisms, such as KPI monitoring dashboards, which allow for real-time tracking of performance data using business intelligence tools (Kaplan and Norton, 1992), employee and customer feedback systems through surveys, focus groups, and sentiment analysis to gather qualitative insights (Pyzdek and Keller, 2014), and benchmarking against industry best practices, comparing performance metrics with industry leaders to identify gaps and areas for improvement (Hammer and Champy, 1993). For well-performing processes, promotional and marketing strategies can amplify their impact, ensuring they remain competitive. For underperforming processes, targeted interventions should include forecasting models, which use historical data and predictive analytics to anticipate future performance trends (Montgomery, 2017), targeted training and competency development to ensure employees possess the necessary skills to optimize performance (Pyzdek and Keller, 2014), financial resource allocation adjustments through data-driven budgeting to improve operational efficiency, and continuous improvement initiatives (such as Kaizen and Six Sigma) to implement structured methodologies that reduce waste and variation (Pyzdek and Keller, 2014). Benchmarking against top-performing organizations also allows for the adoption of best practices (Hammer and Champy, 1993). Recent advancements in AI and ML have revolutionized the way organizations analyze feedback and implement continuous improvement. AI-driven systems can detect inefficiencies in real-time using anomaly detection algorithms, automate decision-making processes for enhanced agility, and optimize predictive models to anticipate future challenges and recommend proactive solutions (Kaplan and Norton, 1992).

RESULTS AND DISCUSSION

Urban governance is a complex and dynamic process that requires systematic performance management to ensure efficiency, effectiveness, and citizen satisfaction. This study examines a hypothetical municipality, referred to as Metropolitan City X, which comprises four municipal organizations responsible for delivering a range of public services. These organizations include: Urban Planning and Development Authority (UPDA): Focused on urban development and infrastructure planning. Public Transportation and Mobility Department (PTMD): Responsible for managing public transportation systems and mobility solutions. Environmental and Waste Management Authority (EWMA): Tasked with environmental protection and waste management services. Digital Transformation and Smart Governance Unit (DTSGU): Dedicated to implementing digital innovations and smart governance initiatives. These organizations collectively serve the 22 distinct districts of Metropolitan City X, each with unique needs and challenges. By analyzing their performance, this study aims to provide insights into improving urban governance and enhancing service delivery across the city. According to the proposed model, an expert team is formed, consisting of PM experts with specialized knowledge in performance

Table 4: BSC of the organizations

DMUs	Learning and growth	Internal processes	Stakeholder management	Resource management
UPDA	Training hours per employee Employee satisfaction and retention rate	Project completion rate (%)	Public satisfaction with urban planning (%)	Budget adherence for urban development projects (%)
	Innovation rate in urban planning projects	Compliance with zoning regulations (%)	Customer feedback on housing projects (%)	Cost efficiency in infrastructure projects
		Sustainability of infrastructure development (%)	Community engagement rate	Return on investment (ROI) for urban development projects
PTMD	Employee training and development hours per employee	Service frequency and coverage (trips per day, area served)	Customer satisfaction with public transportation (%)	Cost per passenger mile
	Innovation in mobility services (% of new technology adoption)	Fleet maintenance and downtime rate (%)	On-time performance rate (%)	Revenue generation from public transport (%)
	Employee satisfaction and retention rate (%)	Integration of sustainable transport solutions (%)	Passenger complaints and resolution rate (%)	Cost savings from energy-efficient transportation
EWMA	Employee training and development hours per employee	Waste diversion rate (%)	Public satisfaction with waste management services (%)	Cost per ton of waste processed
	Innovation in waste management technologies (%)	Compliance with environmental regulations (%)	Compliance with waste segregation policies (%)	Revenue from recycling programs (%)
	Employee engagement and retention rate (%)	Operational efficiency in waste collection and disposal (tons per truck per day)	Response time to environmental complaints (hours)	Operational cost reduction in waste management (%)
DTSGU	Employee training hours in digital skills per employee	Digital service delivery speed (average response time, hours)	Citizen satisfaction with digital government services (%)	Cost per digital project implemented
	Innovation rate in digital governance (number of new technologies implemented)	System uptime and reliability (%)	Adoption rate of digital services by citizens (%)	Return on investment (ROI) from smart governance initiatives (%)
	Employee engagement and retention rate (%)	Digital solution integration rate (%)	Public trust in smart governance systems (%)	Operational cost reduction from digitalization (%)

measurement and improvement, as well as domain specialists from each organization. Indicators are developed, BSCs are constructed, and the weights of the indicators are calculated using the AHP method. Table 4 presents the BSCs.

The EFQM model, a non-prescriptive and widely recognized framework, is selected as an excellent tool for self-assessment. This model is structured around three core categories: Direction, Execution, and Results, each of which is further divided into specific subcriteria. These categories and their corresponding subcriteria are as follows: Direction: Purpose, vision, and strategy: Defining the organization's mission, long-term vision, and strategic objectives. Organizational culture and leadership: Fostering a culture of excellence and ensuring effective leadership. engaging stakeholders: Building strong relationships with stakeholders to align interests and expectations. Execution: Creating sustainable value: delivering value to stakeholders in a sustainable

Table 5: EFQM Subcriteria in BSC

Learning and growth	Internal processes	Stakeholder management	Resource management
Purpose, vision, and strategy	Driving performance and transformation	Engaging stakeholders	Managing resources and the ecosystem
Organizational culture and leadership		Customer results	Business results
Creating sustainable value		People results Society results	

Table 6: Score of the organizations in each aspect of the BSC

DMUs	Learning and growth	Internal processes	Stakeholder management	Resource management
DTSGU	60.80%	70.00%	30.00%	10.00%
PTMD	42.53%	37.94%	18.71%	65.09%
EWMA	38.62%	77.81%	38.51%	67.93%
UPDA	35.41%	52.12%	33.17%	55.30%

manner. driving performance and transformation: Implementing initiatives to enhance performance and drive organizational change. Managing resources and ecosystem: Optimizing the use of resources and managing the broader ecosystem effectively. results: Customer results: Measuring outcomes related to customer satisfaction and service delivery. People results: Evaluating employee engagement, development, and well-being. Society results: Assessing the organization's impact on society and the environment. Business results: Analyzing financial and operational performance. Table 5 is provided to illustrate how these subcriteria of the EFQM model align with the most relevant aspects of the BSC. This alignment ensures a comprehensive evaluation framework that integrates the strengths of both models, enabling organizations to assess their performance holistically and identify areas for improvement.

Additionally, customer survey questions have been incorporated into the stakeholder management aspect of the BSC. This integration ensures that the perspectives and feedback of stakeholders, particularly customers, are systematically captured and analyzed as part of the performance evaluation process. By aligning the organization's BSC with specialized KPIs and including stakeholder input through customer surveys, the framework provides a comprehensive and balanced view of performance. This approach not only measures internal efficiency and effectiveness but also reflects external stakeholder satisfaction, enabling a more holistic assessment of organizational success. The AHP is employed to determine the weights of KPIs within each aspect of the BSC for every organization. This method ensures a systematic and objective approach to prioritizing KPIs based on their relative importance. The data for the KPIs are collected, verified, and aggregated according to Table 6, ensuring accuracy and consistency in the evaluation process. By applying AHP, the weights assigned to each KPI reflect their significance in achieving the strategic objectives of the organization.

In this step, DEA is utilized to calculate the efficiency of the organizations. The DEA model is structured by considering the learning and growth, and internal processes aspects as inputs, while stakeholder management and resource management are treated as outputs. This configuration allows for a comprehensive evaluation of how effectively organizations convert their internal capabilities and processes into tangible outcomes related to stakeholder satisfaction and resource utilization. The results of the DEA analysis are presented in Table 7, which provides a clear overview of the efficiency scores for each organization. These scores highlight the relative performance of the organizations in leveraging their inputs to achieve desired outputs. By identifying efficient and inefficient units, the DEA results offer valuable insights into areas where improvements can be made to enhance overall performance. This step is crucial for understanding the operational effectiveness of the organizations and guiding strategic decision-making.

According to the obtained results, both the

Table 7: Efficiency of the organizations

DMUs	Efficiency
DTSGU	67.35%
PTMD	46.03%
EWMA	100.00%
UPDA	100.00%

Table 8: Score of the districts in each aspect of the BSC

DMUs	Learning and growth	Internal processes	Stakeholder management	Resource management
1	61%	70%	30%	10%
2	43%	38%	19%	65%
3	39%	78%	39%	68%
4	35%	52%	33%	55%
5	55%	55%	6%	40%
6	68%	26%	97%	1%
7	63%	52%	65%	88%
8	89%	22%	17%	73%
9	57%	57%	10%	44%
10	44%	26%	72%	39%
11	14%	51%	84%	58%
12	42%	17%	8%	43%
13	4%	90%	98%	95%
14	41%	30%	53%	93%
15	77%	18%	47%	28%
16	24%	21%	55%	51%
17	13%	28%	95%	6%
18	88%	66%	19%	20%
19	59%	96%	85%	3%
20	52%	81%	69%	61%
21	49%	31%	99%	38%
22	9%	11%	15%	93%

EWMA and the UPDA achieved the same efficiency score and were ranked first. The DTSGU secured the second rank, while the PTMD was ranked third. This scenario highlights a limitation of the DEA model, as it often fails to differentiate between units that achieve the same efficiency score, leading to tied rankings. This issue can become more pronounced as the number of DMUs increases, making it difficult to provide a clear and actionable ranking. For further investigation, consider a scenario where 22 DMUs (districts) are evaluated using the DEA model. Table 8 provided scores of the districts in each aspect of the BSC, and Table 9 provided the efficiency of the organizations.

According to Table 9, DMUs 6, 13, 17, and 22 have all achieved 100% efficiency and are tied for the first rank based on the DEA results. While the DEA model effectively identifies efficient and inefficient DMUs, it faces a significant limitation: it cannot provide a detailed ranking when multiple units achieve the same efficiency score. This issue becomes particularly problematic as the number of DMUs increases, leading to tied rankings and reduced clarity in performance evaluation. This limitation highlights the necessity of integrating complementary methods, such as TOPSIS, to refine the evaluation process. This method offers granular insights into the relative performance of each DMU by considering multiple criteria and assigning distinct scores and rankings. By combining the strengths of the DEA model with TOPSIS, organizations can overcome the shortcomings of the DEA model and achieve a more comprehensive and differentiated assessment. This integrated approach enables better-informed decision-making, ensuring that resources are allocated effectively and performance improvements are targeted where they are needed most. In this part, the TOPSIS method is employed to rank the organizations, ensuring that

Table 9: Efficiency of the districts

DMUs	Efficiency	Rank
1	13%	14
2	27%	11
3	25%	13
4	26%	12
5	9%	17
6	100%	1
7	48%	8
8	47%	8
9	11%	15
10	86%	4
11	84%	5
12	32%	9
13	100%	1
14	72%	7
15	80%	6
16	93%	3
17	100%	1
18	10%	16
19	26%	12
20	30%	10
21	97%	2
22	100%	1

Table 10: Weights of the aspects of the BSC

Aspects	Learning and Growth	Internal processes	Stakeholder management	Resource management
Weights	15.00%	25.00%	35.00%	25.00%

each organization is assigned a distinct and specific rank. To accomplish this, the AHP technique is utilized to determine the weights of the criteria, as illustrated in Table 10. This approach ensures a systematic and objective ranking process based on the calculated weights and performance metrics.

The TOPSIS method (Hwang and Yoon, 1981) operates by calculating the geometric distance of each alternative from both the positive ideal solution (PIS) and the negative ideal solution (NIS). The optimal alternative is selected based on two key criteria: it should have the shortest geometric distance from the positive ideal solution and the longest geometric distance from the negative ideal solution. This dual-criterion approach ensures that the chosen alternative is the most favorable, balancing proximity to the best possible outcomes and distance from the worst possible outcomes. The constructed BSC serves as the decision matrix, denoted as ($D=\left[k_{ij}\right]_{mn}$) where the rows ($i=1,\ldots,m$) show alternatives (organizations) and columns ($j=1,,n$) show criteria (aspects). Each element x_{ij} in the matrix indicates the score of the i-th alternative with respect to the j-th criterion. To normalize the decision matrix, the vector normalization method is applied, as described by Eq. 6:

$$R_{ij}=\frac{k_{ij}}{\sqrt{\sum_{i=1}^{m}k_{ij}^{2}}},\quad \text{for all } i=1,,m,\quad j=1,,n. \tag{6}$$

In this equation, R_{ij} represents the normalized value of x_{ij}. This normalization process ensures that the criteria are scaled uniformly, allowing for a fair and consistent comparison across different alternatives. Now, by multiplying each normalized value R_{ij} by its corresponding weight W_j, the weighted normalized matrix is constructed by Eq. 7:

$$V_{ij}=W_jR_{ij}. \tag{7}$$

Then, the positive ideal solution, the maximum value of alternatives in each attribute, ($V^{+} = V_1^{+}, V_2^{+}, \dots, V_n^{+}$) and the negative ideal solution, minimum value of alternatives in each attribute ($V^{-} = V_1^{-}, V_2^{-}, \dots, V_n^{-}$) can be constructed. So, the separation measure can be calculated by Eq. 8 and by Eq. 9

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} \left(V_{ij} - V_j^{*}\right)^2}, \text{ for all } i = 1, \dots, n. \quad (8)$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} \left(V_{ij} - V_j^{-}\right)^2}, \text{ for all } i = 1, \dots, n. \quad (9)$$

Now we can calculate the relative closeness to the ideal solution by Eq. 10

$$C_i^{+} = \frac{S_i^{-}}{S_i^{+} + S_i^{-}}, \quad \text{for all } i = 1, \dots, n. \quad (10)$$

So, the final ranking is achieved, and we can use the ranking for future actions.

Table 11 and Table 12 present the final scores derived from the TOPSIS method. According to the results, EWMA achieves the top rank with a score of 94.67%, while UPDA secures the second rank with a score of 46.86%. Interestingly, the DEA method assigns 100% efficiency to both organizations, indicating that DEA is unable to differentiate between their performance levels.

According to the tables, DEA assigned 100% efficiency to the 6th and 17th DMUs, while TOPSIS ranked them 20th and 21st, respectively. The primary reason for this significant discrepancy lies

Table 11: TOPSIS score of the organizations

DMUs	Score
EWMA	94.67%
UPDA	46.86%
PTMD	39.17%
DTSGU	38.13%

Table 12: TOPSIS score of the districts

DMUs	Score	Rank
1	87%	10
2	86%	13
3	89%	5
4	87%	8
5	86%	14
6	82%	20
7	89%	4
8	87%	12
9	87%	11
10	85%	18
11	87%	6
12	85%	15
13	94%	1
14	87%	7
15	85%	17
16	85%	16
17	82%	21
18	87%	9
19	90%	3
20	90%	2
21	83%	19
22	34%	22

in the fundamental differences between the two methodologies. DEA evaluates efficiency based on the ratio of outputs to inputs, meaning that DMUs 6 and 17 achieved high efficiency due to their excellent performance in stakeholder management, despite poor performance in resource management. However, TOPSIS takes a more comprehensive approach by considering multiple criteria and does not overlook such imbalances, providing a more detailed and nuanced evaluation of each DMU. Similarly, DMU 22 was rated 100% efficient by the DEA but received only a 34% score and a 22nd rank by TOPSIS. This inconsistency arises because DEA incorporates the scores of learning and growth, as well as internal processes, into the input section, which allowed DMU 22 to achieve full marks despite its poor performance in other aspects. In contrast, TOPSIS evaluates each DMU by comparing its performance across all criteria to the best-performing DMU, thereby addressing such conflicts and offering a more balanced assessment. On the other hand, DMU 13 was rated 100% efficient by the DEA and also secured the first rank with a 94% score in TOPSIS, indicating strong overall performance. The remaining conflicts between DEA and TOPSIS rankings can be attributed to the same underlying reasons: DEA's focus on input-output ratios often overlooks imbalances in specific criteria, while TOPSIS provides a more holistic and detailed comparison across all aspects. This demonstrates that TOPSIS offers a more informative and reliable ranking system, particularly when evaluating DMUs with varying strengths and weaknesses across multiple dimensions.

CONCLUSION

This study introduced an eight-step conceptual performance management model that addressed the limitations of existing frameworks by offering a comprehensive, visually intuitive, and step-by-step approach. The model began with forming a team of performance management experts and domain specialists, followed by integrating the organization's mission, vision, strategies, processes, and stakeholder perspectives into a structured system of KPIs. These KPIs were categorized into specialized KPIs (derived from core processes and strategic factors), self-assessment KPIs (based on excellence models), and customer survey KPIs (capturing external feedback). The KPIs were mapped into the BSC framework, with weights determined using the AHP. Scores were assigned to KPIs, and data were collected, cleaned, and stored for analysis. Mathematical tools like DEA and TOPSIS were used to calculate efficiency and rank organizations, followed by implementing corrective actions for continuous improvement. A case study of a hypothetical municipality demonstrated the model's applicability, revealing discrepancies between DEA and TOPSIS results, which were analyzed to highlight its ability to deliver nuanced and actionable outcomes. By combining data-driven decision-making with a holistic evaluation framework, this model enabled organizations to achieve continuous improvement and strategic alignment, making it a valuable tool for enhancing performance across diverse contexts.

AUTHOR CONTRIBUTIONS

K. Fahimi performed the literature review, conducted the conceptual model and numerical results, compiled the data, analyzed and interpreted the data, and prepared the manuscript text and edition. A. Alaeddini, M. Poramezan, and F. Kabuli performed the literature review and applied the model and designed the BSC.

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CONFLICT OF INTEREST

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the authors have witnessed ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy.

PUBLISHER NOTE

ABBREVIATIONS

PM	Performance Management
MBO	Management by Objectives
KPIs	Key Performance Indicators
BSC	Balanced Scorecard
KRIs	Key Result Indicators
RIs	Result Indicators
PIs	Performance Indicators
JUSE	Union of Japanese Scientists and Engineers
TQM	Total Quality Management
MBNQA	Malcolm Baldrige National Quality Award
EFQM model	European Foundation for Quality Management model
SCOR model	Supply Chain Operations Reference Model
SCC	Supply Chain Council
MCDM	Multi-Criteria Decision-Making
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
AHP	Analytical Hierarchical Process
ANP	Analytic Network Process
VIKOR	Vise Kriterijumska Optimizajica I Kompromisno Resenje
PROMETHEE	Preference Ranking Organization METHod for Enrichment Evaluation
DEA	Data Envelopment Analysis
DMUs	Decision-Making Units
CSFs	Critical Success Factors
CI	Consistency Index
CR	Consistency Ratio
RI	Random Index
$A=\left[a_{ij}\right]$	Pairwise comparison matrix.
a_{ij}	Amount of preference of element i to element j.

W_i	Weight of element i
$(W_1,..,W_n)$	Vector of weights.
C	An n-dimensional column vector.
$CV=[cv_i]_{1*n}$	Consistency value.
γ_{max}	Maximum eigenvalue.
CI	Consistency index.
RI	Average random index.
Z_o	Efficiency score of the DMU
j , o	Set of DMUs
i	Set of inputs
r	Set of outputs
x_{ij}	Amount of input i for DMU j
y_{rj}	Amount of output r for DMU j
u_r	Weight output r
v_i	Weight input i
PDCA cycle	Plan-Do-Check-Act cycle
SPC	Statistical Process Control
BPR	Business Process Reengineering
ML	Machine Learning
AI	Artificial Intelligence

SWOT	Strengths, Weaknesses, Opportunities, and Threats
UPDA	Urban Planning and Development Authority
PTMD	Public Transportation and Mobility Department
EWMA	Environmental and Waste Management Authority
DTSGU	Digital Transformation and Smart Governance Unit
PIS	Positive ideal solution
NIS	Negative ideal solution
$D=[k_{ij}]_{mn}$	Decision matrix.
k_{ij}	A score of alternatives i in criteria j.
R_{ij}	Normalized amount of x_{ij}.
V_{ij}	Weighted normalized amount of x_{ij}.
$(V^+=V_1^+,V_2^+,\ldots,V_n^+)$	The maximum value of alternatives in each attribute.
$(V^-=V_1^-,V_2^-,\ldots,V_n^-)$	The minimum value of alternatives in each attribute.
S_i^+	Positive separation measure.
S_i^-	Negative separation measure.

C_i^+	Relative closeness to the ideal solution.

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