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Optimizing Healthcare Business Processes with Process Mining Software: A Comparative Analysis

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ABSTRACT

This study focuses on the application of process mining in the healthcare sector. Despite its potential to enhance efficiency, reduce costs, and improve patient satisfaction, the selection of process-mining software poses significant challenges due to the diverse nature of healthcare processes and the lack of comprehensive evaluation methods. To bridge this gap, this study employed a hybrid Multi-Criteria Decision-Making (MCDM) approach, integrating the Neural Network-Augmented Analytical Hierarchy Process (NNA-AHP) and Grey Relational Analysis—a technique for Order Preference by Similarity to Ideal Solution (GRA-TOPSIS). The study evaluated process mining software on functionalities, ease of use, cost, technical support, scalability, and security with their respective sub-criteria. The principal results indicate that Disco is the top-performing alternative, followed by Celonis and ProM. Sensitivity analysis was conducted to understand the influence of variations in criteria weights on evaluating alternatives. In the NNA-AHP, Celonis consistently scored the highest. The GRA-TOPSIS method provided performance scores, indicating that higher scores yield better performance. The new hybrid method consolidates evaluations from all methods and offers the most comprehensive and dependable alternative assessment. Disco and its alternatives, Celonis and ProM, are recommended for optimizing healthcare processes. Further research is needed to investigate the integration of NNA-AHP and GRA-TOPSIS in healthcare management, especially in areas beyond business process analysis. This study provides valuable insights for professionals and researchers in the field and contributes to understanding the effectiveness of process mining.

1. Introduction

Process mining has emerged as a valuable tool in healthcare, offering the potential to enhance efficiency, reduce costs, and improve patient satisfaction [1]. Several studies have explored the application of process mining in healthcare, focusing on its potential to improve efficiency, cost, and patient satisfaction [1-5]. However, selecting process-mining software in this context is challenging because of the diverse nature of healthcare processes and the lack of comprehensive evaluation

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methods [6]. The selection of appropriate process mining software poses a significant challenge for healthcare organizations as the market offers more than 47 solutions with varying features and capabilities [7].

Traditional evaluation methods, including the commonly used Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), may not adequately capture the nuances of healthcare environments, leading to suboptimal tool selection decisions [8,9]. A comprehensive framework integrating advanced evaluation methods can address these challenges [10]. Despite these challenges, process mining has been successfully applied in healthcare for process model discovery and evaluation [11]. Multi-criteria decision analysis (MCDA) methods have been explored in healthcare decision-making problems, with hybrid methods being the most widely used [12].

Deep learning methods are promising approaches for process prediction in process mining [13]. However, there is a lack of comprehensive studies that critically evaluate and compare process mining tools in this context. This study addresses this gap by adopting a comparative approach using the Neural Network Augmented AHP and GRA-TOPSIS methods to evaluate and select process mining software tools. This study's methodology is unique in its rigorous and accurate framework.

1.1. Common Healthcare Business Processes

Standard healthcare business processes such as patient registration, appointment scheduling, billing, and claims management, health information management, inventory management, quality assurance, staff scheduling, and management, patient communication, compliance and regulatory reporting, and financial management are essential for the efficient operation of healthcare organizations [9]. These processes can be optimized using various management practices. Process-based management, Lean Six Sigma, continuous improvement models, cost management, and value-based healthcare are recognized worldwide to improve efficiency, reduce waste, and add value to the business [14,15]. Implementing business process management (BPM) in healthcare settings such as Hirslanden AG can enhance the standardization of processes, optimization, and ERP transformation, resulting in improved patient satisfaction, workforce conditions, operational efficiency, and financial performance [16]. Process mining is another essential tool for reducing costs, improving processes, and reducing process time in healthcare organizations [16]. IT systems and comprehensive process management play crucial roles in supporting primary and secondary care processes, optimizing care delivery, and improving the quality of care for patients [15].

1.2. Process mining technique

Process mining, a data analytics approach, has been increasingly applied in healthcare to improve efficiency, reduce costs, and enhance patient satisfaction [3]. It has been used to identify bottlenecks, streamline processes, optimize resource allocation, and automate workflow [17]. Challenges in this application include data quality, algorithm selection, and presentation of results [1]. Process mining has also been used to evaluate healthcare processes using the proposed goal-driven evaluation method [2]. It has been applied to clinical care pathways in primary care, revealing insights and informing service redesigns [18]. A methodology for process mining in healthcare, PM 2 HC, has been developed to provide guidelines for its application [19]. Process mining has been used in cardiology to improve chronic disease management, particularly in the care of cardiovascular diseases [17]. However, privacy concerns in healthcare data have led to the development of privacy-preserving process-mining techniques [20].

According to Kurniati *et al*., [21] process mining in healthcare has forward- and backward-looking perspectives, as shown Figure 1. Discovery creates a model for existing processes and identifies bottlenecks and inefficiencies. Conformance compares the actual process to a predefined model and determines deviations. It evaluates a process's performance over time and detects trends and areas for improvement. The predictive approach predicts the outcomes of a process based on data and identifies potential issues.

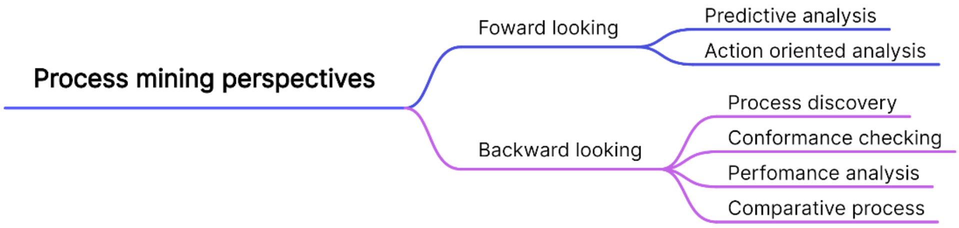

Fig. 1. Perspectives in the Process Mining

Process mining encompasses a range of techniques, including forward and backward locking, each serving different purposes. Forward locking, for instance, is used for predictive and action-oriented analysis, whereas backward locking is employed for process discovery, conformance checking, and performance analysis. The latter is particularly relevant in healthcare and is commonly applied to supplementary data. However, there is a need for more focus on outcomes or prescription data in this context. The most commonly used techniques for analyzing healthcare processes include dotted charts, performance analysis with Petri nets, and performance sequence diagrams [22]. Celonis is a popular process discovery tool that uses formal models for analysis. The log must be related to cases for practical process mining analysis [23]. The process mining parameters can be adjusted to influence the results and output of the assessment. However, the quality of the process data is crucial for deriving values from process-mining techniques. A method for justifying and implementing process mining projects has been developed, including a generic business case framework and an eight-phase methodology [24]. A method and guiding tool for conducting process mining projects has also been proposed [25].

Process mining parameters can be adjusted to influence the results and output of the analysis, and these parameters can vary depending on the mining tool used and the specific goals of the analysis, as shown in Figure 2.

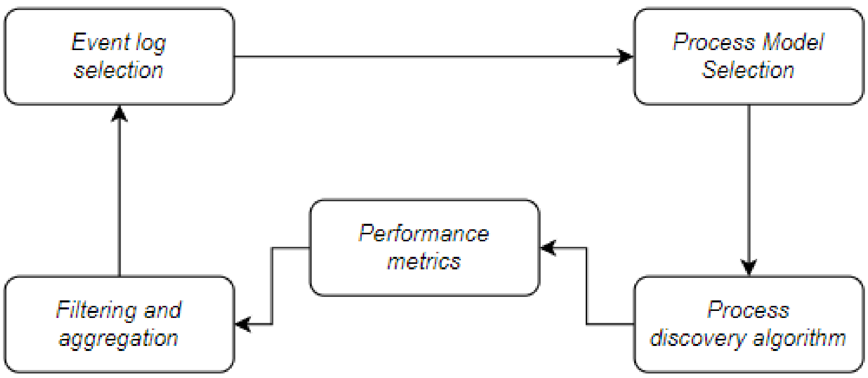

Fig. 2. The Role and Impact of Process Mining Software Tools in Healthcare

to clarify the direct impact of process mining on efficiency, cost reduction, and patient satisfaction in healthcare organizations

1.3. Evaluation criteria for optimal selection of Process Mining Software

Numerous process mining software tools are available, offering distinct functionalities, ease of use, cost considerations, technical support, scalability, and security features. ProM, an open-source tool, offers several techniques albeit with a potential complexity barrier for some users [26]. On the other hand, commercial tools like Celonis, Disco, and My Invenio, are easier to use and focus on data extraction, performance analysis, and scalability [23]. Although, they may offer limited support for implementing custom algorithms [27]. ProM, Disco, and Celonis were discussed in detail in a comparative study [28]. RapidProM, an extension of ProM, allows for the modeling and executing complex process mining workflows [29]. A methodology for comparing process mining tools is proposed, enabling the assessment of their suitability based on various criteria [30], as indicated in Table 1. A website for comparing commercial process mining tools is also available [31].

Table 1
Comparison of authors' tools, evaluation criteria, and conclusions

References	Tools Compared	Evaluation Criteria	Conclusion/Result
[30]	Apromore Community Edition, ProM, Celonis, MyInvenio, and Disco	License, Filtering, Browser-based, Process Animation, etc.	Apromore (22.0%), ProM (21.7%), Celonis (20.3%), MyInvenio (20.3%), and Disco (15.7%). AHP-OS was used for analysis.
[23]	ProM, Disco, Celonis, and My-Invenio	Assisted platform, output model notation, Import log size, Process discovery, etc.	ProM is considered essential but has UI issues. Comparison based on specified parameters.
[32]	Disco, ProM, Celonis	Binary evaluation, Strengths/weaknesses inferred	Disco, ProM, and Celonis are commonly used. Evaluation based on binary decisions.
[33]	ProM, Disco, Celonis	Similar functionality with differences in delivery	All three tools offer similar functionality. Comparison parameters are identical too.
[31]	16 process mining tools	General info, data management, process discovery, Conformance checking, etc.	Distinctions between process mining and related fields blurring. Different tools offer varied capabilities.
[34]	Various software including Selonis, SmartSense, UiPath Process Mining	Criteria: Easy to use, Features, User interface, etc.	Popular software includes Selonis, SmartSense, and UiPath Process Mining. IBM, Software AG, and UiPath have a significant presence.

The research gap lies in the diverse nature of healthcare processes, where existing process-mining software often fails to address the unique complexities, hindering the selection of suitable solutions. There is a lack of comprehensive evaluation methods specific to healthcare, leading to suboptimal tool selection decisions. This highlights the need for tailored evaluation frameworks to leverage process mining in healthcare effectively.

To tackle this challenge, our research will conduct a comparative analysis of various process mining tools. Advanced evaluation methods such as Neural Network Augmented AHP and GRA-TOPSIS will be employed to thoroughly examine and compare these tools. The goal is to provide valuable insights for healthcare organizations seeking to choose the most suitable solution. Each process mining tool to offer guidance on optimizing their use in healthcare settings will be evaluated.

2. Methodology

This research employs a hybrid MCDM approach, neural network-augmented AHP, and GRA-TOPSIS. This study was structured around three key stages. The research method for this study involved a literature review that identified a gap in the evaluation and comparison of process mining software tools in healthcare business operations. The study's unique methodology involved using the Neural Network Augmented AHP and GRA-TOPSIS methods to address this gap. These methods were used to assess the impact of process mining on efficiency, cost, and patient satisfaction in healthcare and to determine the optimal process mining software for healthcare business processes, as indicated in Figure 3.

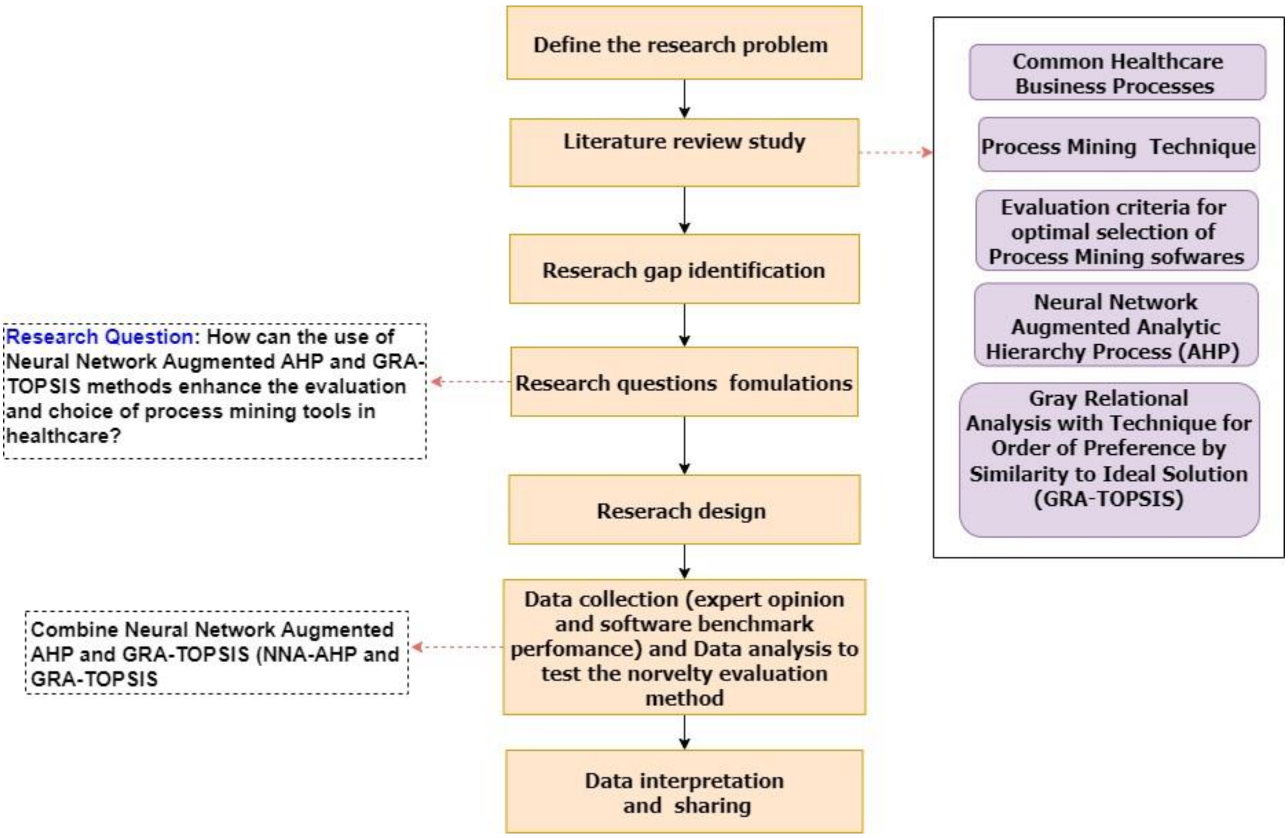

Fig. 3. Research Methodology plan

2.1. Optimization Model of Process Mining software for health care systems

Based on previous research, a novel decision-making model integrating Neural Network Augmented AHP (NNA-AHP) and GRA-TOPSIS is proposed. The model involves problem formulation, AHP analysis, and Neural Network Augmentation. It is validated and subjected to sensitivity analysis. The results were then combined with the GRA-TOPSIS analysis for decision-making, as indicated in Figure 4. Altuzarra's Bayesian prioritization procedure was used to enhance this model for AHP-GDM.

Ludermir's methodology for global optimization of neural networks, Tagliarini's discussion on the design of feedback neural networks, Matsuda's neural network model for decision-making based on AHP, and Davies' adaptive AHP were all incorporated into the model. Additionally, the model is supported by Wang's hybrid genetic algorithm-neural network strategy for simulation optimization, Gee's analytical framework for optimizing neural networks, and Triantaphyllou's comparative study of multi-criteria decision-making methods.

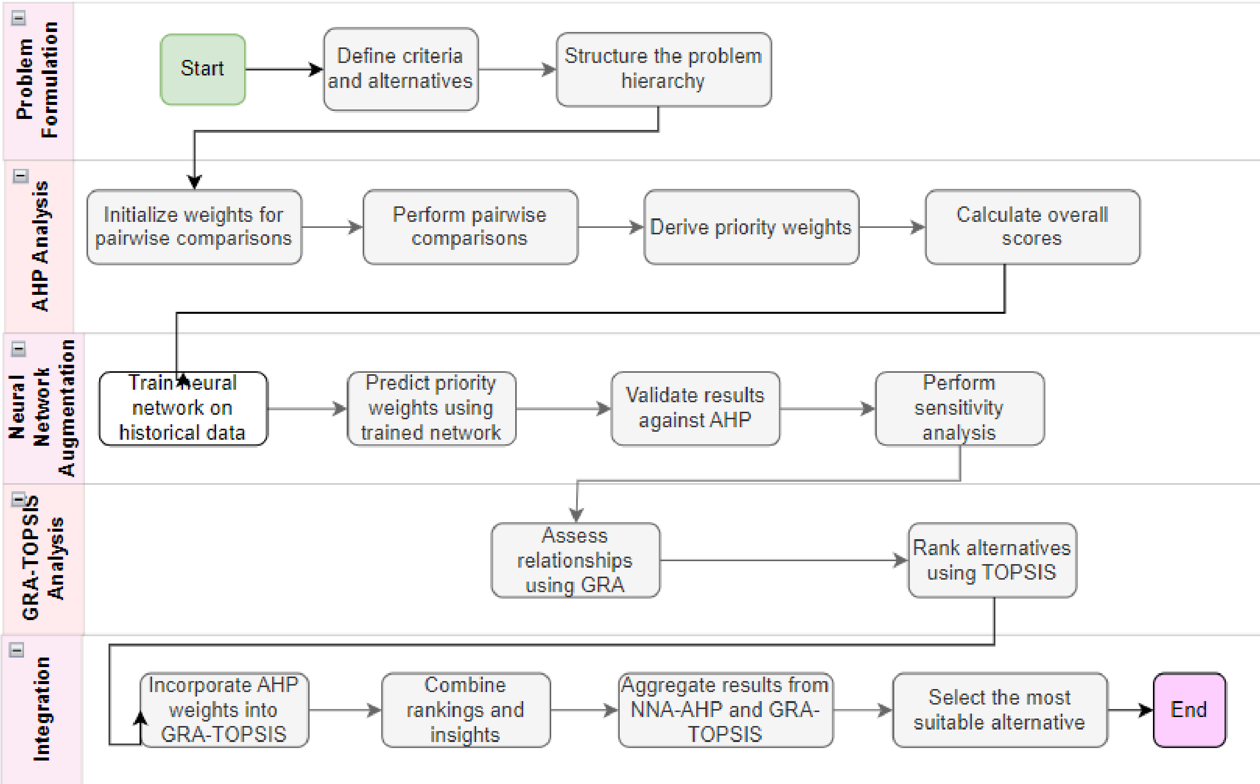

Fig. 4. The implementation steps of NNA-AHP -GRA-TOPSIS

2.2. Problem formulation

Step 1: *Defining Criterion and Alternatives*

In evaluating process mining software for healthcare systems, the proposed mathematical equations for AHP and neural network augmented AHP were improved to incorporate evaluation criteria encompassing functionalities such as Process Discovery, Conformance Checking, Performance Optimization, and Root Cause Analysis. These criteria are weighted based on their significance, along with factors such as Ease of Use (including User Interface and Support & Documentation), cost (Total Cost of Ownership and Other Costs), Technical Support (Availability and Quality), scalability (Performance, Speed, and Integration with Other Systems), and security (Data Protection and Compliance). Appropriate weights are assigned to these criteria and alternatives, such as Disco, Celonis, ProM, ARIS Process Mining, Aprome, IBM Process Mining, and UiPath Process Mining, based on their alignment with the criteria considerations in the decision-making process, as indicated in Figure 5. t $C = \{c_1, c_2, \ldots, c_N\}$ represent the set of criteria for evaluating process mining software for healthcare systems. Let $A = \{a_1, a_2, \ldots, a_M\}$ denotes the set of alternatives (different process mining software options).

Step 2: *Structure the Problem Hierarchy*

This structured approach enables the application of neural network-augmented AHP GRA-TOPSIS to effectively assess and rank alternatives in complex decision scenarios, as indicated in Figure 5. It leverages the combined power of artificial neural networks, the Analytical Hierarchy, and the GRA-TOPSIS Process to enhance accuracy and handle intricate decision problems.

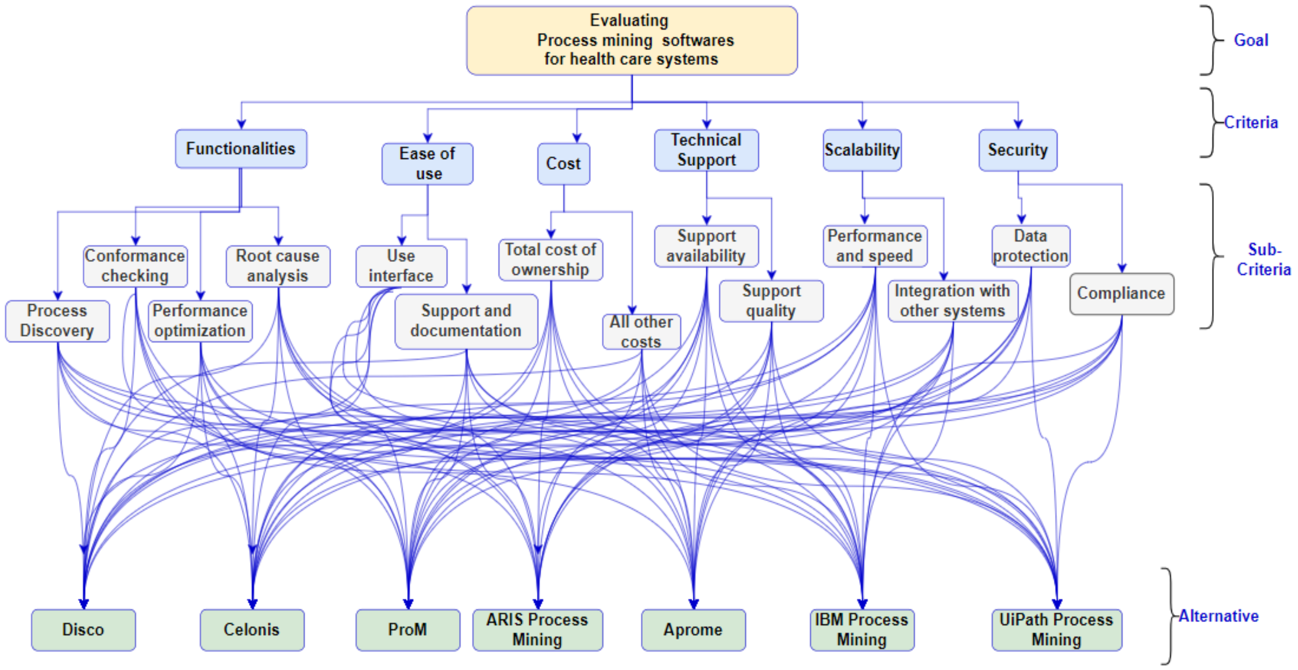

Fig. 5. Hierarchical structure of criteria and alternatives

2.3. AHP Analysis in evaluating process Mining software for healthcare systems

Multiple studies have examined the application of AHP in assessing process mining software for healthcare systems, covering a broad range of perspectives and methodologies. Elhadjamor and Ghannouchi [35] and Dallagassa *et al.,*[11] highlight the potential of process mining in healthcare, emphasizing the need for data integration and compliance evaluation. The use of AHP in health technology assessment was discussed in Improta *et al.*, [36], that presented a dynamic AHP framework. Martinez-Millana *et al.*, [37] and Batra *et al.*, [38] applied AHP to evaluate healthcare systems, with the former focusing on the features of a process mining dashboard and the latter using a fuzzy AHP strategy [39]. Elhadjamor and Ghannouchi [35] and Mesabbah *et al.,* [40] proposed models for evaluating operational process variables and automated simulation modeling in healthcare, respectively, with the former incorporating data visualization techniques. Pereira *et al.*, [19] developed a methodology for applying process mining in healthcare, emphasizing stakeholder involvement and KPI evaluation.

Step 1: *Initialize Weights for Pairwise Comparisons*

Assigning weights to pairwise comparisons typically involve seeking expert opinions on the relative importance of criteria or alternatives. These weights were derived from a range of sources, including historical data, benchmarking the performance of process mining software, and input from one healthcare expert and four process mining software users, who provided their input on the AHP software through group opinion.

Step 2: *Pairwise Comparison of Criteria*

The calculation of Priority Weights for Criteria Professionals uses pairwise comparisons to evaluate the significance of various criteria, employing a Saaty scale that spans from 1 to 9 for this purpose. A matrix 'A' is created to aid in determining accurate weights for criteria to guide future decision-making processes. Matrix A is constructed through Equation (1), where A_{ij} signifies the pairwise assessment between criteria 'i' and 'j' for $ij \in \{1,2,\dots,n\}$ and A_{ii}= 1 and et $A_{ij} = {}^{1}/_{A_{ij}}$, with n denoting the total number of criteria within the comparison matrix [41].

$$\mathrm{A} = \begin{bmatrix} 1 & \mathrm{A}_{12} & \dots & \mathrm{A}_{1\mathrm{n}} \\ {}^{1}/_{A_{12}} & 1 & \dots & \mathrm{A}_{2\mathrm{n}} \\ \vdots & \vdots & \ddots & \vdots \\ {}^{1}/_{A_{1n}} & {}^{1}/_{A_{2n}} & \dots & 1 \end{bmatrix} \tag{1}$$

Step 3: Calculation of Priority weights for criteria

Priority weights for each criterion were determined by averaging preference values obtained from expert judgments, and the average preference values were obtained from five experts of Process Mining software users. The calculation involves normalization to ensure that the sum of all weights equals 1.00. This process includes normalizing the pairwise comparison matrix and computing the eigenvalues and eigenvectors to derive the relative weights.

a) Normalize the pairwise comparison matrix by dividing each element by the sum of each column of the matrix 'A' to make it equal to 1.
b) Compute the eigenvalues and eigenvectors of the normalized matrix. The eigenvector (w) corresponding to the maximum eigenvalue (λ_{max}) provides the relative weights and provides the following relations

$$Aw = (\lambda_{max})\ \mathrm{w} \tag{2}$$

Step 4: Consistency Test

The consistency test in AHP is essential for evaluating the degree of consistency within the decision matrix. This involves calculating the Consistency Ratio (CR) by comparing the Consistency Index (CI) with a Random Index (RI). An acceptable CR is typically less than 0.1 or 10%, indicating consistency. If the CR exceeds this threshold, it signifies inconsistencies and requires reevaluation.

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{3}$$

Where the calculation of CI is performed by

$$\mathrm{CI} = \frac{(\lambda_{\mathrm{max}} - \mathrm{n})}{\mathrm{n} - 1} \tag{4}$$

2.4. Neural Network Augmented AHP

Neural Network Augmented AHP, a method that combines artificial neural networks (ANNs) with the Analytic Hierarchy Process (AHP), has been shown to improve decision accuracy and handle complex decision problems. This integration involves a forward propagation process, an output layer, and AHP integration, resulting in combined weighted aggregation. This method also incorporates consistency measures using neural-network predictions [42]. The use of ANNs in this context is supported by research on the performance of different activation functions in deep learning. The application of this method in transportation cost prediction was demonstrated using trapezoidal neutrosophic fuzzy AHP and ANNs [43]. Integrating ANNs with AHP makes the decision-making process more robust and adaptive. Using the values of the alternatives i against criteria j a neural network with N input nodes representing criteria and M output nodes representing the weights. Let A_{ij} be the value of criterion j for alternative i. Train Neural Network using historical data from the AHP values of criteria and alternatives.

i) Forward Propagation

$$h_i{}^{(1)} = \sigma\left(\begin{bmatrix} \sum_{j=1}^{N} w_{1j}{}^{(1)} A_{1j} + b_1{}^{(1)} \\ \sum_{j=1}^{N} w_{2j}{}^{(1)} A_{2j} + b_2{}^{(1)} \\ \vdots \\ \sum_{j=1}^{N} w_{Mj}{}^{(1)} A_{Mj} + b_M{}^{(1)} \end{bmatrix}\right) \tag{5}$$

Where $h_i{}^{(1)}$is the output of the hidden layer for alternative i, $w_{ij}{}^{(1)}$ is the weight connecting input node j to hidden node i, $b_i{}^{(1)}$ is the bias for hidden nodes i and σ is the activation function.
Output Layer

$$w_{ik}{}^{(2)} = \sigma\left(\begin{bmatrix} \sum_{i=1}^{M} w_{i1}{}^{(2)} h_i{}^{(1)} + b_1{}^{(2)} \\ \sum_{i=1}^{M} w_{i2}{}^{(2)} h_i{}^{(1)} + b_2{}^{(2)} \\ \vdots \\ \sum_{i=1}^{M} w_{iK}{}^{(2)} h_i{}^{(1)} + b_K{}^{(2)} \end{bmatrix}\right) \tag{6}$$

Where $w_{ik}{}^{(2)}$ is the weight connecting hidden node i to output node k, $b_k{}^{(2)}$ is the bias for output node k

ii) AHP Integration

Let W_k be the weight obtained from the neural network for criteria k and A_{ij} be the pairwise comparison matrix.

Neural Network Weighted Aggregation

$$\text{Neural \_Agg}_i = \sum_{k=1}^{N} W_k \,.\, A_{ik} \tag{7}$$

Traditional AHP Weighted Aggregation

$$\text{AHP \_Agg}_i = \sum_{j=1}^{N} A_{ij} \,.\, A_{ij} \tag{8}$$

Combined Weighted Aggregation

$$\text{Combined \_Agg}_i = \lambda.\,\text{Neural\_Agg}_i + (1-\lambda).\,\text{AHP \_Agg}_i \tag{9}$$

Where λ is a parameter controlling the influence of the neural network.

Consistency Measures (using Neural Network Predictions)

Assume the neural network has been trained to predict the consistency of pairwise comparisons.

$$\text{Consistency\_Prediction}_{ij} = \text{Neural\_Consistency\_predictor}(\mathrm{A_i}) \tag{10}$$

2.5. Grey Relational Analysis with Technique for Order of Preference by Similarity to Ideal Solution (GRA-TOPSIS)

Grey Relational Analysis with Technique for Order of Preference by Similarity to Ideal Solution (GRA-TOPSIS) is a valuable multi-criteria decision-making method in the healthcare industry. It has been successfully applied in various domains, including healthcare, to evaluate and rank hospitals based on performance criteria. The ability of the method to handle both qualitative and quantitative data is beneficial in this industry [44]. In other sectors, the TOPSIS method has been used for supplier selection with extensions such as the Intuitionistic Fuzzy TOPSIS method [45] and the OWAD–TOPSIS method [46]. These studies demonstrated the versatility and effectiveness of the TOPSIS method in various decision-making contexts.

The evaluation was initiated by setting criteria and assigning weights. A decision matrix of strategies and criteria was created and normalized to compare strategy fairs. Grey relational coefficients measure the association between alternatives and criteria. The positive and negative ideal solutions were determined to assess the potential performance of each strategy. The GRA-TOPSIS method calculates the similarity to the positive ideal solution, allowing the ranking of strategies based on their overall performance. The following steps were performed.

Step 1: Recall the evaluation criteria and weights from stage C.

The evaluation criteria and their respective weights are represented as vectors.

$$[\mathrm{w_1}, \mathrm{w_2}, \ldots, \mathrm{w_m}] \tag{11}$$

Where m is the number of evaluation criteria and $\mathrm{w_I}$ is the weight assigned to criterion i

Step 2: Recall a decision matrix with the alternatives and criteria from stage C.

This step involves creating a decision matrix with process-mining alternatives and criteria. Each alternative is assigned a score based on the requirements using a decision matrix. Decision matrix X comprises m rows and n columns, where m represents the number of alternatives and n represents the number of criteria. Each matrix element $\mathrm{A_{ij}}$ shows the evaluation of alternative $\mathrm{A_i}$ using criterion $\mathrm{C_i}$. The higher the value of $\mathrm{A_{ij}}$, the better the performance of alternative $\mathrm{A_i}$ with respect to criterion $\mathrm{C_j}$ [47,48].

$$X = \{A_{ij}\} = \begin{array}{c} C_1 \\ C_2 \\ \vdots \\ C_m \end{array} \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1n} \\ A_{21} & A_{22} & \dots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{m1} & A_{m2} & \dots & A_{mn} \end{bmatrix} \tag{12}$$

Step 3: The decision matrix is normalized.

The normalized decision matrix is calculated by dividing each element in the decision matrix by the sum of the corresponding columns multiplied by their weights [49,50] as stated in Eq. (13) and Eq. (14)

$$Y = \{y_{ij}\} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \tag{13}$$

Where

$$y_{ij} = \frac{A_i}{\sum_1^m w_i\, A_{ij}} \quad \text{for } i = 1, 2, \dots, m \text{ and } j = 1,2, \dots, n \tag{14}$$

Step 4: Determine Positive-Ideal Solution (PIS) denoted by Y^+ and the Negative-Ideal Solution denoted by Y^-.

The equations for calculating the PIS, $Y^+ = (y_1{}^+, y_2{}^+, \dots, y_n{}^+)$ and NIS $Y^- = (y_1{}^-, y_2{}^-, \dots, y_n{}^-)$ are shown in Eq. (15) and Eq. (16).

$$y_j{}^+ = \max y_{ij} (i = 1,2, \dots, m, j = 1,2, \dots, n), \tag{15}$$

$$y_j{}^- = \min y_{ij} (i = 1,2, \dots, m, j = 1,2, \dots, n) \tag{16}$$

Calculation of the separation of each alternative from the PIS and NIS [8,51].

To determine how far apart each choice is from the PIS and NIS, the Euclidean distance is used, as stated in Eq. (17) and Eq. (18).

$$D_j{}^+ = \|y_i - Y^+\|_2 = \sqrt{\sum_{j=1}^n \left(y_{ij} - y_j{}^+\right)^2} \quad (i = 1,2, \dots, m) \tag{17}$$

$$D_j{}^- = \|y_i - Y^-\|_2 = \sqrt{\sum_{j=1}^n \left(y_{ij} - y_j{}^-\right)^2} \quad (i = 1,2, \dots, m) \tag{18}$$

Where $D_j{}^+$ Represents the distance between alternatives y_i and Y^+ . $D_j{}^-$ represents the distance between alternatives y_i and Y^-.

Step 5: Estimation of grey relational coefficients

Let PIS and NIS be the reference sequences and let each strategy be determined. The Grey relation coefficients for each strategy to the PIS and NIS can then be calculated using [48,52]:

$$r_{ij}^{+} = \frac{\min_i \min_j |y_j^{+} - y_{ij}| + \zeta \max_i \max_j |y_j^{+} - y_{ij}|}{|y_j^{+} - y_{ij}| + \zeta \max_i \max_j |y_j^{+} - y_{ij}|} = \frac{\zeta v_j}{v_j - y_{ij} + \zeta v_j} \tag{19}$$

$$(i = 1,2, \dots, m, j = 1,2, \dots, n)$$

$$r_{ij}^{-} = \frac{\min_i \min_j |y_j^{-} - y_{ij}| + \zeta \max_i \max_j |y_j^{-} - y_{ij}|}{|y_j^{-} - y_{ij}| + \zeta \max_i \max_j |y_j^{-} - y_{ij}|} = \frac{\zeta v_j}{v_j - y_{ij} + \zeta v_j} \tag{20}$$

$$(i = 1,2, \dots, m, j = 1,2, \dots, n)$$

where ζ is the distinguishing coefficient, ζ ∈ [0, 1]; ζ = 0.5 is usually applied following the rule of least information.

Step 6: Calculate the merged results and grey relational degree [8].

$$r_{ij}^{+} = \frac{1}{n} \sum_{j=1}^{n} r_{ij}^{+} (i = 1,2, \dots, m), \tag{21}$$

$$r_{ij}^{-} = \frac{1}{n} \sum_{j=1}^{n} r_{ij}^{-} (i = 1,2, \dots, m), \tag{22}$$

Eq. (23) and Eq. (24) are used to execute D_i^{+}, D_i^{-}, r_i^{+} and r_i^{-} dimensionless processing on and generate integrated results.

$$q_i^{+} = \beta \frac{D_i^{+}}{\max (D_i^{+})} + \gamma \frac{r_i^{+}}{\max (r_i^{+})} \ (i = 1,2, \dots, m) \tag{23}$$

$$q_i^{-} = \beta \frac{D_i^{-}}{\max (D_i^{-})} + \gamma \frac{r_i^{-}}{\max (r_i^{-})} \ (i = 1,2, \dots, m) \tag{24}$$

where β is a measure of the closeness of an alternate solution to an ideal option in terms of proximity. γ represents the influence of closeness on the grey relational degree of ideal and alternate solutions. β, γ ∈ [0, 1], β + γ = 1.

Step 7: Calculate and grade the options' closeness [52].

$$C_i = \frac{q_i^{+}}{q_i^{+} + q_i^{-}} \ (1,2, \dots, m) \tag{25}$$

Closeness was specified to establish the ranking order of all options. The closeness coefficient compares an option's proximity to the positive ideal solution with its proximity to the negative ideal solution. A higher value of C_i value suggests a closer match to the positive ideal solution.

2.6. Combine Neural Network Augmented AHP and GRA-TOPSIS

A combined approach of AHP and GRA-TOPSIS, augmented with neural networks, has been shown to enhance the evaluation and recommendation process for selecting software in various domains. Rajak and Shaw, [53] applied this approach to mHealth application selection, while Czekster *et al.,* [54] used it for ERP software selection in healthcare facilities. Boonsothonsatit *et al.,* [41] extended this to technology selection in hospital medication dispensing processes. Ulkhaq *et al.,* [55] and Liu *et al.,*[56], both explored the combination of AHP with other methods for car and Digital Twin Design software selection, respectively. By integrating neural networks into AHP, the decision-making model can benefit from the neural network's ability to learn complex patterns and relationships within the data. This can help assign more accurate weights to the criteria considered in the evaluation process, such as functionality, user-friendliness, technical support, cost-effectiveness, scalability, and security.

3. Results and Analysis

3.1. Importance relative weights %

Criteria weights were used to evaluate alternatives. These weights indicated the importance of each criterion in the evaluation as indicated in Table 2. A higher weight signifies greater importance, while a lower weight indicates less criticality. The following criteria and associated sub-criteria were used to evaluate and select an optimal process mining software. These criteria include functionalities (Process Discovery, performance checking, performance optimization, Flexibility, Root cause analysis, and social network analysis) and Ease of Use (user interface, training and onboarding in resources, customization and integration capabilities, support, and documentation).

Table 2
Importance relative weights

	Functionalities	Ease of use	Cost	Technical Support	Scalability	Security
Weight	25	13	18	13	13	18

Table 3 presents expert-assigned scores for various process mining alternatives across criteria such as functionalities, ease of use, cost, technical support, scalability, and security. Higher scores indicate better performance or suitability for each criterion.

Table 3
Alternatives Scores against the criteria

Alternative	Functionalities	Ease of use	Cost	Technical Support	Scalability	Security
Disco	5.976	21.724	9.420	17.172	47.578	4.561
Celonis	9.684	32.951	8.211	17.907	25.640	12.813
ProM	7.078	11.881	16.592	11.608	10.465	6.036
ARIS Process Mining	4.313	12.043	4.974	7.216	7.934	6.150
Aprome	4.888	14.180	5.168	6.619	12.225	6.469
IBM Process Mining	4.723	20.054	5.357	7.025	13.281	6.476
UiPath Process Mining	4.531	22.409	3.738	6.968	11.453	6.651

3.2. Ranking Based on AHP Analysis

Based on the Traditional AHP analysis results, the process mining software choices were ranked in order of priority, as shown in Table 4. Celonis emerged as the most preferred alternative with a priority of 17.48%, followed by Disco at 16.54% and IBM Process Mining at 10.35%. ProM, UiPath Process Mining, Aprome, and ARIS Process Mining followed closely with priorities ranging from 10.26% to 8.52%. The findings from the AHP analysis highlight Celonis as the top-ranking option, providing valuable insights into the relative advantages and perceived efficacy of each software option within the field of process mining.

Table 4
Ranked Results After Traditional AHP Analysis

Alternative	Celonis	Disco	IBM Process Mining	ProM	UiPath Process Mining	Aprome	ARIS Process Mining
Score	17.48%	16.54%	10.35%	10.26%	9.78%	9.08%	8.52%

3.3. Sensitivity Analysis

A sensitivity study was carried out, and Figure 6 shows how differences in the criteria weights affected the assessment of the alternatives in several dimensions. Alternatives show more variation in their results in areas like Scalability and Ease of Use, even if they typically perform highly in categories like Technical Support and Security. This variability highlights possible trade-offs and possibilities for development by emphasizing how sensitive alternatives are to modifications in particular criteria. The consistency ratio (CR) provides decision-makers with a thorough grasp of alternative performance to support strategic decision-making and ensures the validity of the evaluation process.

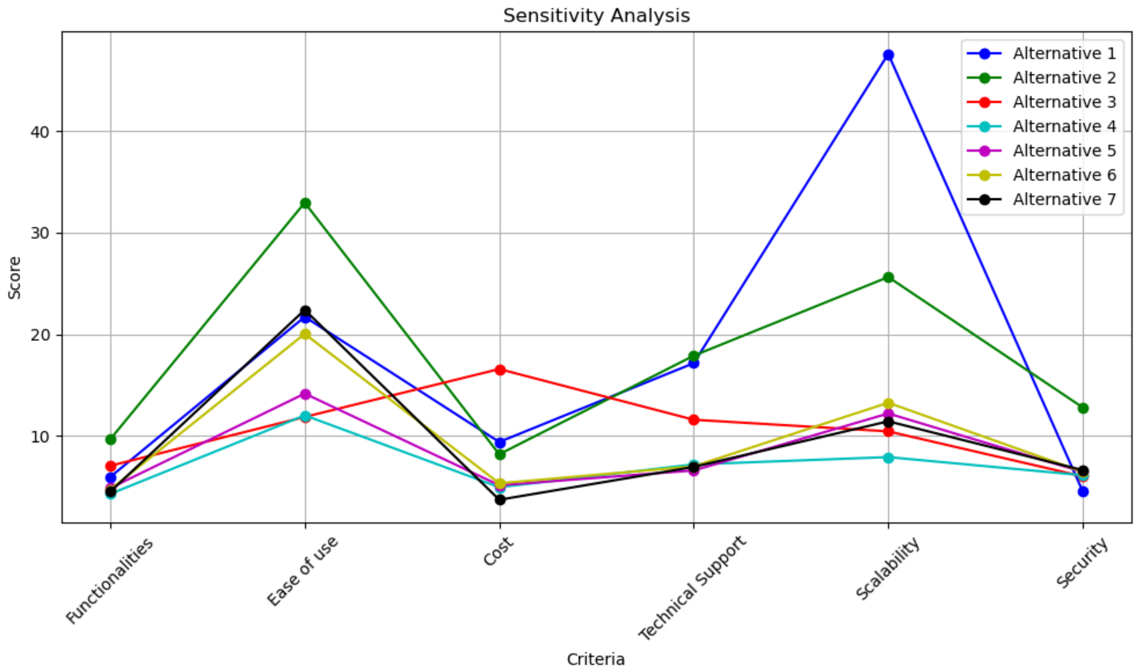

Fig. 6. Sensitivity analysis

3.4. Results of Neural Network Augmented AHP

The neural network technique utilizes traditional AHP methodology to analyze outcomes from a Neural Network Augmented Analytic Hierarchy Process (AHP), as shown in

Table **5** and Figure 7, aiming to enhance decision-making processes. When process mining tools are analyzed using various aggregating techniques, Celonis outperforms in Neural Network aggregating, Traditional AHP Aggregation, and Combined Weighted Aggregation. Celonis achieves top results in all categories: 11.2606393 in Combined Weighted Aggregation, 0.30368052 in Traditional AHP Aggregation, and 22.21759808 in Neural Network Aggregation. As the best-performing process mining tool across the evaluated criteria and aggregation approaches, Celonis's consistent performance highlights its resilience across various assessment frameworks.

Table 5
Results from the NNAHP

Criteria	Neural Network Aggregation	Traditional AHP Aggregation	Consistency Predictions	Combined Weighted Aggregation
Disco	18.3632	0.2765	0.0281	9.3199
Celonis	22.2176	0.3037	0.0288	11.2606
ProM	16.3177	0.1795	0.0324	8.2486
ARIS ProceMining	9.7630	0.0564	0.0800	4.9097
Aprome	10.8293	0.0687	0.0447	5.4490
IBM Process Mining	11.5375	0.0821	0.0594	5.8098
UiPath Process Mining	10.9716	0.0794	0.0387	5.5255

The analysis in Figure 7 shows how the aggregate technique selection significantly influences the overall scores assigned to each process mining tool. While standard AHP aggregation often yields lower scores compared to neural network aggregation, a hybrid approach provides a more balanced view by utilizing the advantages of both techniques while minimizing their drawbacks. Achieving dependable combined scores necessitates modifying consistency forecasts. The evaluation's requirements and goals should be carefully considered when selecting an aggregate approach.

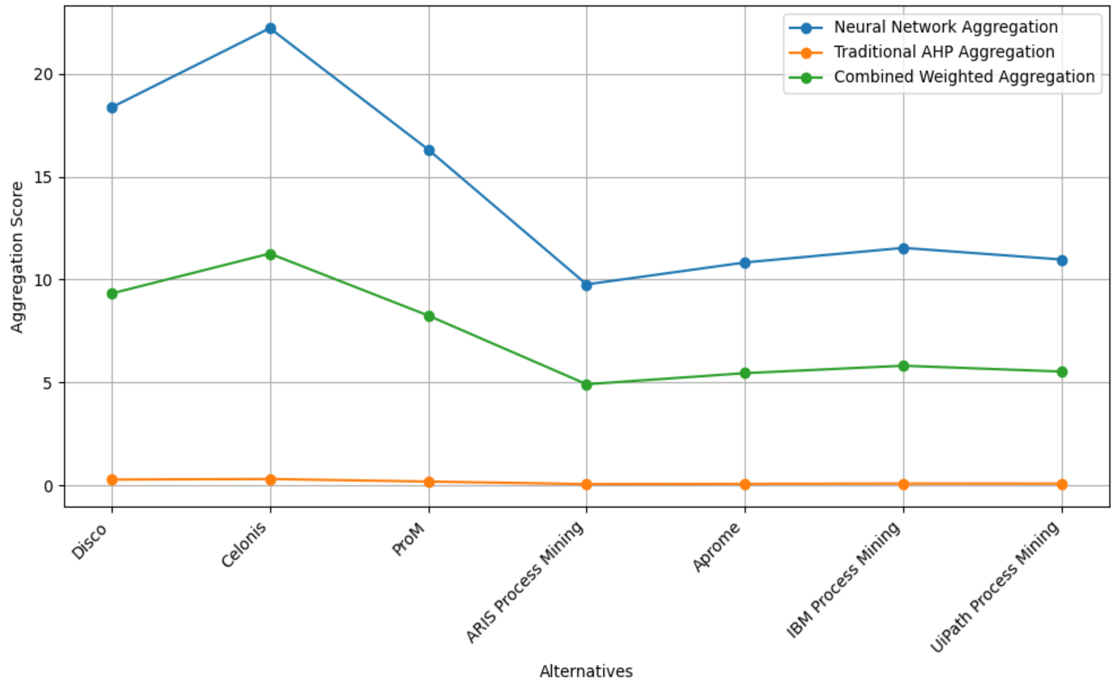

Fig. 7. Comparison of Aggregation Methods for Alternatives

3.5. GRA -TOPSIS Results

Table 6 presents the performance of various alternatives (Disco, Celonis, ProM, etc.) across different criteria (Functionalities, Ease of Use, Cost, etc.), with scores normalized to a standard scale. Higher scores indicated better performance.

Table 6
Normalized Decision Matrix

Alternative / Criteria	Functionalities	Ease of Use	Cost	Technical Support	Scalability	Security
Disco	3.6268298	2.08819745	3.1717	2.99585318	4.8104934	1.67015217
Celonis	5.87721215	3.16738143	2.7646	3.1240824	2.59239671	4.69187892
ProM	4.29563275	1.14204907	5.5865	2.0251493	1.05809016	2.21026935
ARIS Process Mining	2.61755638	1.15762115	1.6747	1.25891431	0.80218703	2.252014
Aprome	2.96652344	1.36303811	1.7401	1.15476079	1.23603939	2.36882578
IBM Process Mining	2.86638507	1.9276704	1.8037	1.22559216	1.34280892	2.37138905
UiPath Process Mining	2.74986041	2.15404238	1.2586	1.21564786	1.15798438	2.43547075

Table 7 provides insights into the distance of each alternative from both the Positive-Ideal Solution (PIS) and Negative-Ideal Solution (NIS) across various criteria, such as functionalities, ease of use, cost, technical support, scalability, and security. Positive-Ideal Solution (PIS): represents the ideal value for each criterion, indicating the best possible performance. Negative-ideal Solution (NIS): represents the worst values for each criterion, indicating the least desirable performance.

Table 7
Distance from Positive-Ideal Solution (PIS)and Negative-Ideal Solution (NIS)

	Functionalities	Ease of Use	Cost	Technical Support	Scalability	Security
Positive-Ideal Solution (PIS)	5.8772	3.1674	5.5865	3.1241	4.8105	4.6919
Negative-Ideal Solution (NIS)	2.6176	1.142	1.2586	1.1548	0.8022	1.6702

Table 8 displays the Grey Relational Coefficients (GRC) for each alternative in positive and negative contexts. Grey Relational Analysis (GRA) is a method used to analyze the correlation between factors. The coefficient (Positive) represents the degree of correlation between each alternative and the positive reference, indicating how closely each alternative resembles the ideal performance. The coefficient (Negative) represents the degree of correlation between each alternative and the negative reference, indicating how distant each alternative is from the worst-case scenario.

Table 8
Grey Relational Coefficients (Positive) and (Negative)

	Disco	Celonis	ProM	ARIS Process Mining	Aprome	IBM Process Mining	UiPath Process Mining
Coefficient (Positive)	0.4390	0.5000	0.4054	0.3273	0.3419	0.3482	0.3352
Coefficient (Negative)	0.2286	0.2085	0.2358	0.5000	0.4597	0.4281	0.4284

Average Grey Relational Coefficients

i) Positive: 0.38529892866221144
ii) Negative: 0.35558773188903997

Table 9 presents the closeness of each alternative to the ideal solution, calculated based on dimensionless scores. Higher closeness values indicate a better overall performance relative to the perfect solution.

Table 9
Closeness of options

	Disco	Celonis	ProM	ARIS Process Mining	Aprome	IBM Process Mining	UiPath Process Mining
Closeness	0.4642	0.4256	0.4838	0.6399	0.6212	0.6082	0.615

Figure 8 compares the performance of different alternative evaluation methods (Celonis, Disco, IBM Process Mining, ProM, UiPath Process Mining, Aprome, and ARIS Process Mining). The methods compared include Traditional AHP, Neural Network Aggregation, Traditional AHP Aggregation, Combined Weighted Aggregation, and Ranked based on GRA - TOPSIS. The new method is the result of the average score of the results of all the methods. It can be observed from Figure 8 that Disco seems to have the highest score among the alternatives.

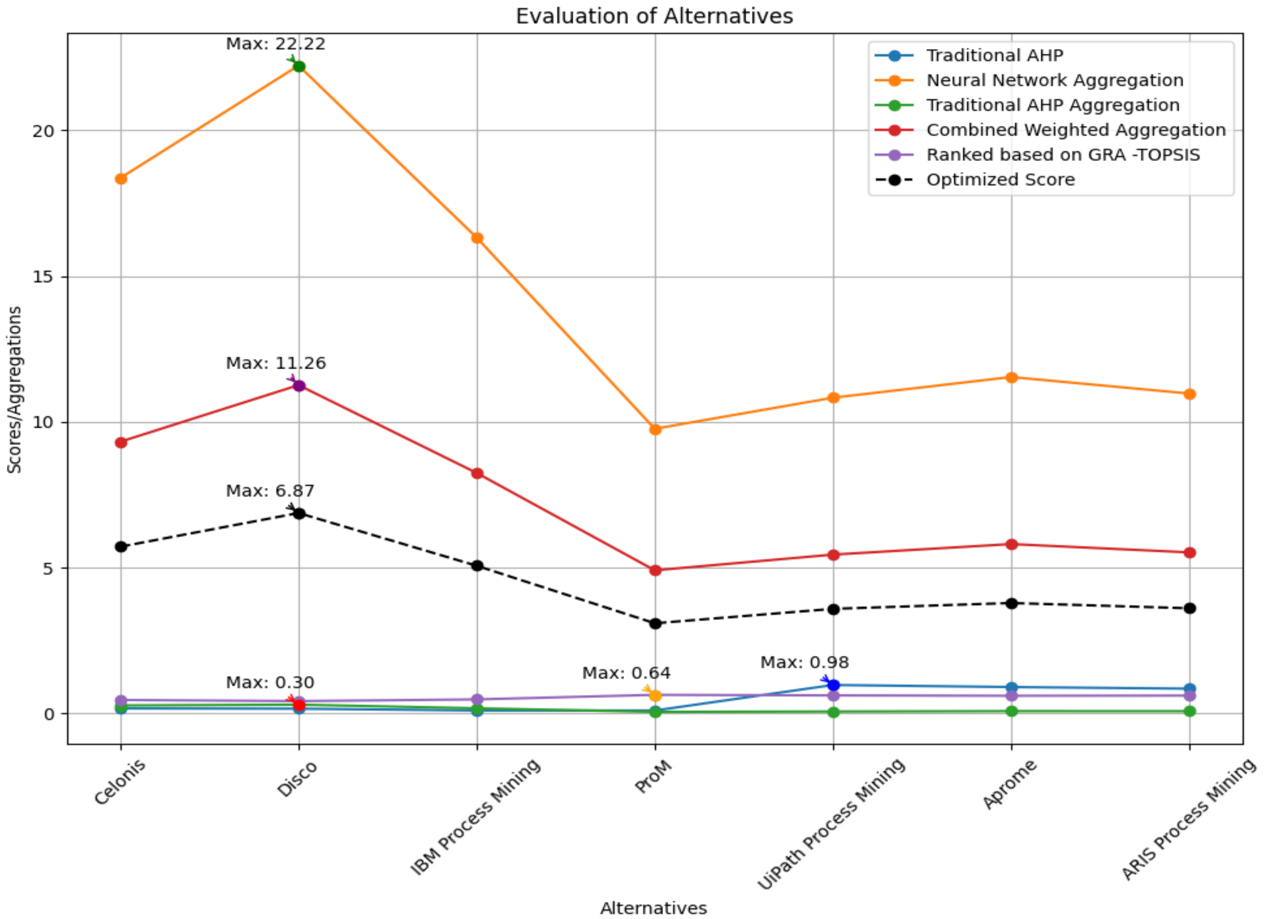

Fig. 8. Comparative Evaluation of Alternative Solutions Using Multiple Methodologies

The evaluation results provide valuable insights into the performance of different alternatives across various methodologies. One alternative, "Disco," consistently achieves the highest scores in multiple evaluation techniques. It scores the highest in three categories: Neural Network Aggregation (22.22), Traditional AHP Aggregation (0.304), and Combined Weighted Aggregation (11.26) and achieves a score of 6.87 in a new optimized method. This indicates the robustness and effectiveness of "Disco" across various assessment frameworks. Another alternative, "UiPath Process Mining," obtains the highest score (0.978) in the Traditional AHP category, highlighting its strength in that specific methodology. Furthermore, "ProM" scores notably well with 0.640 in the GRA-TOPSIS method, demonstrating its competitiveness in this approach.

4. Conclusion

This study focuses on optimizing healthcare business processes by applying process mining software within the healthcare sector. Utilizing methodologies such as Neural Network Augmented Analytic Hierarchy Process (NNA-AHP) and Grey Relational Analysis - Technique for Order Preference by Similarity to Ideal Solution (GRA-TOPSIS), Disco emerged as the top-performing software solution, with Celonis and ProM demonstrating commendable capabilities.

Based on these findings, implementing Disco for healthcare process optimization is recommended, due to its superior performance. Celonis and ProM have also been proposed as viable alternatives for organizations seeking process-mining solutions within the healthcare sector. The study's limitations include subjective weighting, potential bias in results, and absence of user feedback, underscoring the need for further research to enhance understanding of process mining in healthcare.

Continued research is encouraged to explore integrating NNA-AHP and GRA-TOPSIS methodologies in other areas of healthcare management. Such endeavors promise to enhance decision-making processes and improve operational efficiency within healthcare organizations.

Author contributions

Research problem, M.M.M.; Conceptualization, M.M.M., I.B.; Methodology, M.M.M.; Software, M.M.M.; Validation, M.M.M., I.B.; Formal analysis, M.M.M., L.P. and I.B.; Investigation, M.M.M.; Resources, M.M.M., L.P. and I.B.; Data curation, M.M.M.; Writing, M.M.M., L.P. and I.B.; Reviewing and editing, M.M.M., I.B.; Visualization, M.M.M., L.P. and I.B.; Supervision, I.B.; All authors have read and approved the published version of the manuscript.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author, M.M.M, upon reasonable request.

Conflicts of Interest

The authors declare no competing financial, professional, or personal interests.

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