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BIG DATA ANALYTICS SOFTWARE SELECTION WITH MULTI-CRITERIA DECISION-MAKING METHODS FOR DIGITAL TRANSFORMATION

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Abstract

In the process of transitioning to digital businesses, managers are faced with numerous decision-making challenges across various domains. This complexity poses a significant hurdle for traditional businesses seeking to embrace digital transformation. To address this challenge, the Preference Selection Index (PSI) and Additive Ratio Assessment (ARAS) methods are utilized for selecting Big Data Analytics (BDA) software, employing multi-criteria decision-making (MCDM) approaches. With a scenario involving 8 alternatives and 7 criteria, the PSI method is employed to establish the weights of the criteria. Subsequently, the ARAS method is utilized to rank the alternatives. The analysis identifies "Ease of Use" as the criterion with the highest importance weight (0.1464), while "Data Workflow" emerges as the least significant criterion (0.1378). Based on the highest utility degree (0.9548), the fifth alternative was identified as the most suitable big data analytics software for this scenario. Furthermore, the proposed method's applicability is validated through comparative analysis with five different MCDM methods, reinforcing the reliability of the obtained results.

Keywords: *Digital business, Digital transformation, Big data analytics, Multi-criteria decision-making.*

DİJİTAL DÖNÜŞÜM İÇİN ÇOK KRİTERLİ KARAR VERME YÖNTEMLERİ İLE BÜYÜK VERİ ANALİTİĞİ YAZILIM SEÇİMİ

Öz

Dijital işletmelere geçiş sürecinde, yöneticiler çeşitli alanlarda çok sayıda karar verme zorluğuyla karşı karşıya kalmaktadır. Bu karmaşıklık, dijital dönüşümü benimsemek isteyen geleneksel işletmeler için önemli bir engel teşkil etmektedir. Bu zorluğun üstesinden gelmek için, çalışmada Çok Kriterli Karar Verme (ÇKKV) yaklaşımlarından faydalanılarak Büyük Veri Analitiği (BVA) yazılımı seçmek için Tercih Seçim Endeksi (PSI) ve Eklemeli Oran Değerlendirme (ARAS) yöntemleri kullanılmıştır. Sekiz alternatif ve yedi kriter içeren bir senaryoda, kriterlerin ağırlıklarını belirlemek için PSI yöntemi kullanılmıştır. Daha sonra, alternatifleri sıralamak için ARAS yöntemi kullanılmıştır. Analiz sonucunda "Kullanım Kolaylığı" en yüksek önem ağırlığına (0.1464) sahip kriter olarak belirlenirken, "Veri İş Akışı" en az öneme sahip kriter (0.1378) olarak ortaya çıkmıştır. En yüksek fayda derecesine (0.9548) göre, beşinci alternatif bu senaryo için en uygun büyük veri analitiği yazılımı olarak belirlenmiştir. Ayrıca, önerilen yöntemin uygulanabilirliği beş farklı ÇKKV yöntemi ile karşılaştırmalı analiz yoluyla doğrulanarak elde edilen sonuçların güvenilirliği desteklenmiştir.

Anahtar kelimeler: *Dijital işletme, Dijital Ddnüşüm, Büyük veri Analitiği, Çok kriterli karar verme.*

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1. INTRODUCTION

In the 21st century, digitalization has become ubiquitous, profoundly impacting our communication methods and business practices. Digitalization can be referred to as a transformative force for businesses that focus on innovation and efficiency by modifying industries and reconsidering customer expectations (Verhoef et al., 2021: 889). As stated by Ebert and Duarte (2018: 16), digital transformation is a way to produce value for businesses by integrating technology and people. Indeed, it plays a vital role in helping businesses remain competitive in the Internet era (Mergel et al., 2019: 2). Businesses are expected to incorporate digital technologies into their operations. Most of the technologies enabling digital transformation in businesses are computer-related. Analytics, artificial intelligence, big data, blockchain, cloud computing, the Internet of Things, and machine learning are among the digital technologies that businesses could apply for transformation (Stark, 2020: 29). According to Berger (2015: 17-19), there are four main drivers for digital transformation: digital data, connectivity, automation, and digital customer access. The capture, processing, and analysis of digital data enable businesses to make more accurate predictions and informed decisions. Big data and the Internet of Things, in particular, play pivotal roles as enablers for leveraging digital data in this transformative process (Berger, 2015: 20).

Businesses generate an immense amount of data in their operations. This data may include text, videos, images, and audio obtained through machines, social media, sensor networks, cyber-physical systems, and the Internet of Things (Sivarajah et al., 2017: 263). Especially over the last two decades, there has been a significant expansion of data across diverse fields. Due to the rapid increase in global data, the term 'big data' is primarily used to describe vast datasets (Chen et al., 2014: 171). TechAmerica Foundation (2012: 10) defined big data as "*Big Data is a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information.*". However, analyzing vast amounts of data is crucial for businesses to understand customer needs and market trends (Ullah et al., 2018: 3). Due to the variety, velocity, and volume components of big data, capturing, storing, managing, and analyzing it becomes challenging (Sagiroglu and Sinanc, 2013: 42). Therefore, handling big data with traditional software tools within a reasonable time frame becomes impractical (Chen et al., 2014: 173).

Analyzing big data is made possible through methods such as Big Data Analytics (BDA). BDA technology can assist decision-makers in assessing and analyzing large datasets (Pour et al., 2023: 2). As stated by Wamba et al. (2017: 357), BDA can be considered a transformative factor that enhances business efficiency and effectiveness due to its significant operational and strategic capabilities.

Businesses must determine the most suitable technology based on their objectives and investment decisions. However, these objectives and investment decisions can become challenging as the number of alternatives and criteria increases. Multi-Criteria Decision-Making (MCDM) methods play a pivotal role in tackling such decision-making challenges. These methods can address decision-making problems related to various alternatives under specific criteria using a variety of principles. This paper delves into a decision-making challenge associated with selecting BDA software in digital transformation, employing MCDM methodology, specifically utilizing the Preference Selection Index (PSI) and Additive Ratio Assessment (ARAS) methods. The proposed methodology consists of two stages. In the first stage, the PSI method was employed to compute criteria weights (importance levels) and in the second stage, the ARAS method was exploited to rank alternatives. Based on the latest information, it is noteworthy that the PSI and ARAS methods have not been previously employed for this specific purpose in the existing literature. In this regard, the study is positioned to address a significant gap in the literature, particularly in the domain of BDA software selection. The motivation and objectives of the study are outlined below:

● Identifying technologies that facilitate the digital transformation of businesses.

● Demonstrating, based on the definition of big data, that the selection of BDA software, enhancing the effectiveness and efficiency of businesses, constitutes an MCDM problem.

● Providing an extensive literature review of MCDM methods applied in the selection of BDA software.

● Objectively determining the weights of criteria (importance levels) for BDA software selection, a crucial stage in any MCDM problem, through the PSI method.

● Ranking of BDA software alternatives using the ARAS method and a comparison with the results of the PSI method.

The remainder of the paper is organized as follows: The second section presents the related literature. The third section elaborates on the theoretical background of the PSI and ARAS methods. The fourth section provides computational results of the BDA software selection problem. The final section offers an overview of the paper, discusses the analysis results, and outlines the direction for further studies.

2. RELATED LITERATURE

The related literature section is formed into three tiers: The first tier is related to the MCDM applications in the big data domain, and the last couple of tiers are related to the PSI method, and the ARAS method, respectively. Thus, the addressed problem can be analyzed thoroughly.

Lamrini et al. (2023) proposed a parallel Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) approach to expedite decision-making processes in big data context. Maghsoodi (2023) utilized Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and the Višekriterijumsko Kompromisno Rangiranje (VIKOR) method for asset allocation in cryptocurrency markets. Sharma et al. (2023) investigated big data adoption in the tourism and hospitality sectors of emerging economies through the application of the Analytic Hierarchy Process (AHP) and Decision-Making Trial and Evaluation Laboratory (DEMATEL) models. Asemi et al. (2022) assessed difficulties in recommender systems regarding big data and analytical methods, employing fuzzy AHP and a fuzzy inference system. Kim et al., (2022) utilized Geographic Information System (GIS) and AHP method to determine priority control district areas for distribution networks considering big data related to water quality. Gopal et al., (2022) measured the impact of BDA on supply chain performance using the Tomada de Decisão Interativa e Multicritério (TODIM) method. Helmy et al. (2021) evaluated big data processing frameworks and selected the best alternative, employing fuzzy AHP. Lamba and Singh (2018) analyzed the interactions of big data enablers crucial for initiatives in operations and supply chain management, using interpretive structural modeling, fuzzy total interpretive structural modeling, and the DEMATEL method. Sachdeva et al. (2016) selected cloud solutions through the application of intuitionistic fuzzy TOPSIS for the management of big data projects.

The related literature on the PSI method that is used to prioritize criteria weights is summarized as in Table 1.

Table 1: Findings of the PSI method on the related literature

Subject	Paper(s)
Material Selection	Maniya and Bhatt (2010), Samant et al. (2022), Ulutaş et al. (2023), Yadav (2022)
Configuration Selection	Almomani et al. (2013), Duc Trung (2022), Madić et al. (2017), Pathak et al. (2019)
Logistics	Ulutaş, Popovic et al. (2021), Ulutaş and Topal (2022), Ulutaş, Topal et al. (2024)
Subcontractor Selection	Abbasianjahromi et al. (2013)
Performance analysis in sport	Görçün and Küçükönder (2021)
Location Selection	Ulutaş, Balo et al. (2021)
Vehicle Selection	Vahdani et al. (2011)
Machine Selection	Toslak et al. (2023)
Design Selection	Attri and Grover (2015)
Traffic Jam	Magableh and Mumani (2022)
Energy	Biswas et al. (2023)
Tourism	Aksoy and Yetkin Ozbuk (2017)
University Selection	Obeidat et al. (2023)
Personnel Evaluation	Tuş and Aytaç Adalı (2018)
Road Safety	Chen et al. (2023)
Robot Selection	Son and Hieu (2023)
Flood Risk Assessment	Mahmoodi et al. (2023)
Supplier Selection	Pamucar et al. (2024)
Mining	Ampaw et al. (2024)

Table 1 demonstrates the extensive application of the PSI method in various fields of literature. Material selection, for instance, stands out as a significant area of study. In a study conducted by Maniya and Bhatt (2010), the PSI, Graph Theory and Matrix Representation Approach (GTMA), and TOPSIS methods were employed to select materials that align with the requirements of design engineers. Samant et al. (2022) utilized the PSI method to identify the most suitable material for suspension coil springs. Ulutaş et al. (2023) employed a combination of PSI, Method based on the Removal Effects of Criteria (MEREC), Logarithmic Percentage Change-Driven Objective Weighting (LOPCOW), and Multiple Criteria Ranking by Alternative Trace (MCRAT) methods to determine the most efficient natural fibers for insulation materials in construction. Yadav (2022) used the PSI method for the selection of dental restorative composite materials. Additionally, the PSI method has found prominence in configuration selection studies. Almomani et al. (2013) introduced a novel approach to reduce setup times, combining AHP, TOPSIS, and PSI methods. Duc Trung (2022) conducted research to optimize parameter settings for turning operations, utilizing Pareto-Edgeworth Grierson (PEG), PSI, and Collaborative Unbiased Rank List Integration (CURLI) methods. Madić et al. (2017) investigated optimal parameter settings for laser cutting processes through PSI and Taguchi's orthogonal array. Furthermore, the PSI method was applied in diverse contexts. Pathak et al. (2019) proposed a methodology that combines PSI and the particle swarm optimization algorithm to determine three-dimensional scanning process conditions in reverse engineering. Ulutaş, Popovic et al. (2021) addressed a transportation company selection problem using the fuzzy Pivot Pairwise Relative Criteria Importance Assessment (PIPRECIA)-PSI- Combined Compromise Solution (CoCoSo) methodology. Similarly, Ulutaş and Topal (2022) developed a solution approach that incorporates rough Stepwise Weight Assessment Ratio Analysis (SWARA), PSI, and Improved Operational Competitiveness Rating Analysis (IOCRA) methods to model the third-party logistics selection problem in the logistics area. In another study on the logistics sector Ulutaş, Topal et al. (2024) applied the LOPCOW-PSI-Mixed Aggregation by Comprehensive Normalization Technique (MACONT) methodology to assess third-party logistics companies relative to car manufacturing firms. Abbasianjahromi et al. (2013) employed Fuzzy PSI to select subcontractors in the construction sector. Görçün and Küçükönder (2021) assessed football players' performance and quality with Criteria Importance Through Inter-Criteria Correlation (CRITIC), PSI, and Weighted Aggregated Sum Product Assessment (WASPAS) methods. Ulutaş, Balo et al. (2021) investigated the optimal warehouse location for a supermarket by utilizing grey PSI and Proximity Indexed Value

(PIV) methodology. Vahdani et al. (2011) introduced two novel approaches that combine fuzzy TOPSIS and PSI methods to solve the vehicle selection problem, particularly in buses that use alternative fuels. Toslak et al. (2023) employed a hybrid PSI, Statistical Variance (SV), and Measurement of Alternatives and Ranking According to Compromise Solution (MARCOS) methodology to address the machine selection problem to find the most suitable peanut butter machine. Attri and Grover (2015) analyzed the production system life cycle during the design phase using the PSI method. Magableh and Mumani (2022) tackled traffic jam problems through a simulation-based approach that incorporates TOPSIS and PSI methods. Biswas et al. (2023) investigated factors related to the underground coal gasification method in Bangladesh using PSI. Aksoy and Yetkin Ozbuk (2017) conducted research aimed at defining the factors that affect hotel location and ranking hotels based on their locations, utilizing PSI. Obeidat et al. (2023) applied AHP and PSI methods to select doctorate programs among American universities in the field of industrial engineering. Tuş and Aytaç Adalı (2018) analyzed a textile firm's personnel selection process with CRITIC, Combinative Distance-based Assessment (CODAS), and PSI methods. Chen et al. (2023) evaluated the road safety performance of East Asia Summit (EAS) countries using PSI, and PRIDIT methods. Son and Hieu (2023) combined MEREC, MARCOS, and PSI methods to select welding robots. Mahmoodi et al. (2023) prioritized watersheds objectively for flood risk using Mean Weight (MW), PSI, Standard Deviation (SD), Entropy, CRITIC, MEREC, and TOPSIS methods. Pamucar et al. (2024) introduced a PSI-CoCoSo methodology under the Fermatean Fuzzy environment to enhance the efficiency and reliability of green supplier selection within the textile industry. Ampaw et al. (2024) explored effective strategies for addressing illegal mining in Ghana, employing the Linguistic Distribution Assessments (LDA)-PSI-TOPSIS methodology.

The findings of the related literature of the ARAS method that was utilized to rank alternatives are summarized in Table 2.

Table 2: Findings of the ARAS method on the related literature

Subject	Paper(s)
Sustainability	Mostafaeipour and Le (2024), Dehshiri and Firoozabadi (2024), Albawab et al. (2020), Ghenai et al. (2020), Ighravwe and Oke (2019), Medineckiene et al. (2015)
Location Selection	Iordache et al. (2019), Turskis and Zavadskas, (2010), Yilmaz et al. (2023), Zagorskas and Turskis (2020a)
Construction/Building	Turskis and Juodagalvienė (2016), Zagorskas and Turskis (2020b), Zavadskas and Turskis (2010)
Financial Performance	Ozcalici (2022), Ghadikolaei and Esbouei (2014)
Production	Yilmaz and Burdurlu (2023), Sivalingam, Ganesh Kumar et al. (2022)
Personnel Selection	Karabasevic et al. (2016), Keršulienė and Turskis (2012)
Configuration Selection	Sivalingam, Poogavanam et al. (2022), Maheshwari et al. (2021)
Military	Hoan and Ha (2021)
Management	Yapıcı Pehlivan et al. (2018)
Software Development	Ayyıldız and Ekinci (2023)
Robot Selection	Goswami et al. (2021)
Technology Selection	Aytaç Adalı et al. (2023)
Traffic Safety	Badi et al. (2023)

Table 2 exhibits related literature on the ARAS method that has been published recently. It is possible to group these works into specific categories. Sustainability is one of the domains that has garnered substantial attention from researchers, particularly due to its far-reaching implications. Mostafaeipour and Le (2024) sought to formulate renewable energy policies by leveraging SWOT analysis, SWARA, and Gray ARAS, COPRAS, TOPSIS, and MABAC methods. Dehshiri and Firoozabadi (2024) introduced a methodology based on Z numbers to analyze solar energy, addressing uncertainty and reliability through Z-EDAS, Z-TOPSIS, Z-ARAS, Z-COPRAS, Z-SAW, and Z-MABAC methods. Albawab et al. (2020) used SWARA and ARAS methods to rank energy storage technologies. Ghenai et al. (2020) assessed sustainability indicators of renewable energy systems using SWARA, and ARAS methods. Ighravwe and Oke (2019) addressed maintenance strategies for public buildings within a sustainability framework, employing a methodology that integrates SWARA, WASPAS, Fuzzy Axiomatic Design, and ARAS methods. Medineckiene et al. (2015) introduced a novel MCDM approach utilizing AHP and ARAS methods to evaluate building sustainability. Location selection is another prominent domain due to its irrevocable effects on the decisions made by stakeholders. Yilmaz et al. (2023) employed machine learning and MCDM methods to select locations for energy storage systems. Their methodology integrates k-means++, the elbow method, TOPSIS, ARAS, Evaluation based on Distance from Average Solution (EDAS), and Multi-Objective Optimization based on the Ratio Analysis (MOORA). Zagorskas and Turskis (2020a) assessed the locations of pedestrian bridges to mitigate the negative environmental effects of pedestrian and bicycle traffic. Iordache et al. (2019) determined the location for underground hydrogen storage in Romania by integrating interval type-2 hesitant fuzzy sets and the ARAS method. Turskis and Zavadskas, (2010) discussed location selection approaches under a fuzzy environment introducing the ARAS-F method. The ARAS method also finds numerous applications in the construction and building domain. For instance, Zagorskas and Turskis, (2020b) determined priorities for expanding bicycle network using the fuzzy ARAS method. Turskis and Juodagalvienė, (2016) addressed the problem of assessing stair shapes in dwelling houses, employing TOPSIS, EDAS, ARAS, AHP, and SAW methods. Zavadskas and Turskis (2010) introduced the ARAS method in the context of assessing the microclimate of office rooms. Ozcalici (2022) measured financial performance using various MCDM methods, including the ARAS method, while Ghadikolaei and Esbouei, (2014) applied fuzzy AHP and the Fuzzy ARAS methods. In the production field, Yilmaz and Burdurlu (2023) investigated the most suitable wooden furniture joints using CRITIC and ARAS methods. Additionally, Sivalingam, Ganesh Kumar et al. (2022) employed ARAS and CODAS methods to predict an automotive radiator's performance. Karabasevic et al. (2016) proposed a framework to select personnel that combines SWARA and ARAS methods. Additionally, Keršulienė and Turskis (2012) utilized ARAS-F and SWARA methods for architect selection in the personnel selection domain. Meanwhile, Sivalingam, Poogavanam, et al. (2022) investigated the effect of spray-cutting fluid using ARAS and CODAS methods. Maheshwari et al. (2021) determined optimal design parameters for brake discs using SD, EDAS, Complex Proportional Assessment (COPRAS), TOPSIS, and ARAS methods in the field of configuration selection. Hoan and Ha (2021) addressed the fighter aircraft selection problem using ARAS, and Full Consistency Method (FUCOM) methods. Yapıcı Pehlivan et al. (2018) assessed organizational strategy development using Fuzzy AHP, Fuzzy WASPAS, Fuzzy EDAS, and Fuzzy ARAS methods. Ayyıldız and Ekinci (2023) adopted the CRITIC-ARAS methodology to select Six Sigma projects for the software development industry. Goswami et al. (2021) combined ARAS, COPRAS, and TOPSIS methods for robot selection problem analysis. Aytaç Adalı et al. (2023) introduced the neutrosophic extension of the ARAS method, combining it with the N-CRITIC method to handle a technology selection problem. Badi et al. (2023) utilized rough ARAS, WASPAS, COPRAS, and MABAC methods to rank cities in Libya based on traffic safety.

In conclusion, the review of related literature emphasizes the wide-ranging applications of combined MCDM methods in this study, PSI and ARAS, across diverse domains. These methods evolve to adapt to contemporary challenges, offering potential solutions to a broad spectrum of problems. The various extensions of these methods underscore their versatility in addressing uncertainties in varying environments. Furthermore, this study brings a novel contribution by addressing a crucial gap in the resolution of the BDA software selection problem.

3. METHODOLOGY

The methodology employed for selecting BDA software in the context of digital transformation consists of a two-stage approach. These stages can be termed as the weighting phase and the ranking phase. The weighting phase is probably the most crucial process as it significantly impacts the outcomes of the BDA software selection process. Therefore, the methodology for weighting criteria should be elaborately designed to encompass all aspects of the dataset comprehensively. The PSI method was utilized to determine criteria weights objectively. Subsequently, in the second phase, alternatives were ranked based on their performance across these criteria. To perform this process the ARAS method was selected. The adopted methodology is depicted in Figure 1.

3.1. PSI Method

The PSI method was proposed by Maniya and Bhatt (2010). This method stands out for its ease of application among researchers (Görçün and Küçükönder, 2021: 515). Although the PSI method does not require comparing criteria weights (Obeidat et al., 2023: 58) the significance of criteria is determined using a statistics-based approach (Ulutaş, Popovic, et al., 2021: 1230). Thus, criteria are prioritized objectively. This prioritization makes it possible to use the PSI method for ranking alternatives and determining criteria weights (Toslak et al., 2023: 77). The steps of the PSI method are outlined in the following equations (Maniya and Bhatt, 2010: 1786; Maniya and Bhatt, 2011: 543-544):

Step 1: The initial decision matrix *(X)* is constructed. This matrix consists of m alternatives and n criteria. $x_{ij} \in X$ represents the performance of the ith alternative under the jth criterion. The decision matrix is given in Eq. (1).

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

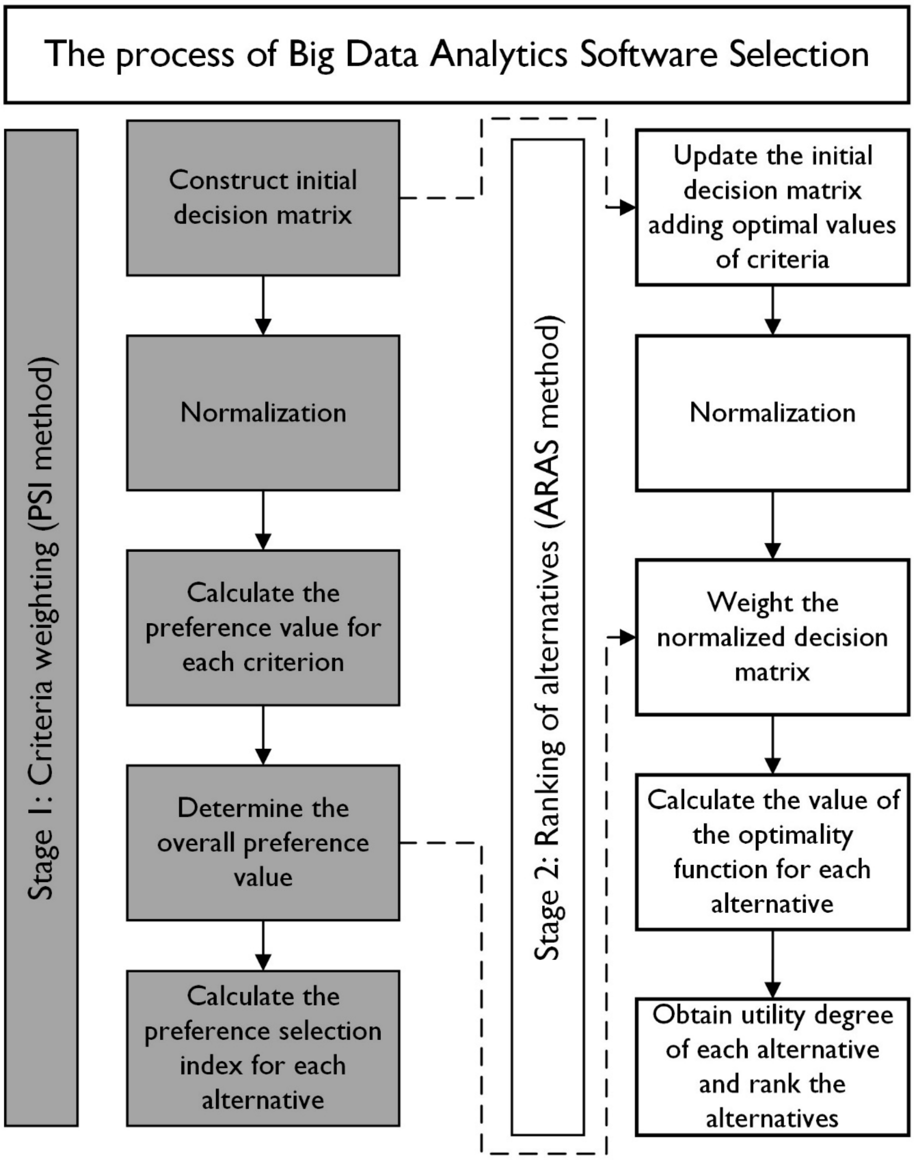

Figure 1: Visualization of the proposed methodology

Step 2: The initial decision matrix is normalized. The normalized decision matrix *(R)* is obtained by being of criteria benefit or cost type. This operation is shown in Eq. (2)-(3) respectively.

$$R_{ij} = \frac{x_{ij}}{x_j^{max}} \quad \text{(If criterion } j \text{ is benefit type)} \tag{2}$$

$$R_{ij} = \frac{x_j^{min}}{x_{ij}} \quad \text{(If criterion } j \text{ is cost type)} \tag{3}$$

Step 3: The preference variation value *(PV_j)* is calculated for each criterion. This value is based on the sample variance concept. The computation of PV_j is as in Eq. (4).

$$PV_j = \sum_{i=1}^{m} \left[R_{ij} - \bar{R}_J\right]^2 \tag{4}$$

Here, $\bar{R}_J$ is the mean of the *j*th criterion of R and it is obtained by Eq. (5).

$$\bar{R}_J = \frac{1}{m}\sum_{i=1}^{m} R_{ij} \tag{5}$$

Step 4: The overall preference value (Ψ_j) is determined. To find this value, deviation from preference value *(Φ_j)* is calculated firstly. Then, the overall preference value is obtained using Eq. (6)-(7) respectively.

$$\Phi_j = 1 - PV_j \tag{6}$$

$$\Psi_j = \frac{\Phi_j}{\sum_{j=1}^{n} \Phi_j} \tag{7}$$

The sum of Ψ_j should equal to 1. Herewith, it is assumed that each element of Ψ_j represents the weight value of a criterion in this paper.

Step 5: The preference selection index *(I_i)* is calculated for each alternative. Subsequently, the alternatives are ranked from the highest to the lowest value. The alternative with the highest value is considered the best. The preference selection index is using Eq. (8).

$$I_i = \sum_{j=1}^{n} \left(R_{ij} \times \Psi_j\right) \tag{8}$$

3.2. ARAS Method

The ARAS method was proposed by Zavadskas and Turskis (2010). The method's conceptual framework originated from the idea that *"simple relative comparisons"* could effectively address complex real-world problems (Zagorskas and Turskis, 2020b: 182). In this respect, the ARAS method ranks alternatives based on their utility function values (Yilmaz et al., 2023: 5). The steps of the ARAS method are outlined in the following equations (Zavadskas and Turskis, 2010: 163-165):

Step 1: The initial decision matrix *(X)* is constructed as in the PSI method. In this matrix x_{0j} represents the optimal value of criterion *j*. The initial decision matrix is presented in Eq. (9).

$$X = \begin{bmatrix} x_{01} & \cdots & x_{0j} & \cdots & x_{0n} \\ x_{11} & \cdots & x_{1j} & \dots & x_{1n} \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \dots & x_{mn} \end{bmatrix} i = 0, \dots, m; j = 1, \dots, n \tag{9}$$

If the optimal value of the *j*th criteria is unknown, x_{0j} can be determined as in Eq. (10)-(11).

$$x_{0j} = \max_i x_{ij} \quad \text{(If criterion } j \text{ is benefit type)} \tag{10}$$

$$x_{0j} = \min_i x_{ij} \quad \text{(If criterion } j \text{ is cost type)} \tag{11}$$

Step 2: The initial decision matrix is normalized. The normalized decision matrix $(\bar{X})$ is obtained by Eq. (12) or (13), depending on the type of criteria.

$$\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \left(\bar{x}_{ij} \in \bar{X}\right) \quad \text{(If criterion } j \text{ is benefit type)} \tag{12}$$

$$\bar{x}_{ij} = \frac{1/x_{ij}}{\sum_{i=0}^{m} 1/x_{ij}} \left(\bar{x}_{ij} \in \bar{X}\right) \quad \text{(If criterion } j \text{ is cost type)} \tag{13}$$

Step 3: The normalized decision matrix $(\hat{X})$ is weighted with the criteria weights (w_j) that were obtained using the PSI method in the previous stage.The elements of this matrix $(\hat{x}_{ij})$are calculated as in Eq. (14).

$$\hat{x}_{ij} = \bar{x}_{ij} w_j, i = 0, \dots, m \tag{14}$$

Step 4: The value of the optimality function (S_i) is calculated for each alternative as presented in Eq. (15).

$$S_i = \sum_{j=1}^{n} \hat{x}_{ij}, i = 0, \dots, m \tag{15}$$

Here, S_0 denotes the value of the optimality function for the optimal alternative. The ranking of alternatives is then determined by comparing the value obtained for each *(S_i,i=1,2,...,m)* alternative with the value of the optimal alternative (S_0 *).*

Step 5: The utility degree *(K_i)* of each alternative is calculated using Eq. (16). The calculations depend on a comparison of the alternative with the optimal alternative. Then, the alternative that has the highest utility degree is considered the best alternative among its rivals.

$$K_i = \frac{S_i}{S_0}, i = 0, \dots, m \tag{16}$$

4. NUMERICAL IMPLICATION

Businesses embark on digital transformations by initially conducting a current situation analysis. Subsequently, they determine a strategy, establish a digital team, and select appropriate digital technologies. Digital technologies enable versatile data management, including instant data access, high-performance data analysis, and efficient transmission of large data volumes. The latest transformations encompass technologies such as cloud computing, big data, artificial intelligence, the Internet of Things, blockchains, digital marketing, social media, and mobile applications for businesses. On the other hand, software developers consistently launch new products with the aim of both drawing in potential customers and fostering enduring relationships with current clients. As a result, the market is flooded with various alternative software options designed to perform similar tasks. To address the decision-making challenges encountered during the identification of suitable software, this paper considers the selection process for BDA software in digital transformation as an MCDM problem.

4.1. BDA Software Selection

This study employs a two-stage approach to identify the most suitable BDA software. To begin, in the first stage, the weights of criteria were calculated using the PSI method, as detailed in Section 3.1. Subsequently, the software alternatives were ranked using the obtained criteria weights employing the ARAS method outlined in

Section 3.2. A comprehensive visualization of the entire process is illustrated in Figure 1, providing an insightful overview of the applied methods. There are a lot of websites on the internet that make it possible to review and compare products such as software, electronic devices, services, etc. The data, including alternatives, criteria, and their review scores, were sourced from a reputable online platform, ensuring the reliability of the information. The rationale behind selecting this dataset is to address a significant gap in the existing literature and mitigate the impact of excessively positive or negative evaluations as the number of evaluations increases. Consequently, it is anticipated that the measurement values of the alternatives under the criteria will better capture the overall level of experience in real-world scenarios.

The problem consists of 8 alternatives and 7 criteria. BDA software alternatives are demonstrated as BDA_i *(i = 1,…,8)* and similarly, criteria are represented as C_j *(j=1,…,7)*. The extent of the criteria can be summarized as follows:

● *Working with real-time data (C_1)* represents the ability to work with real-time data.

● *Data Querying (C_2)* states that querying data from data sources with query languages.

● *Data Visualization (C_3)* serves as a tool that provides informative visuals to its users.

● *Data Workflow (C_4)* is related to automation and integration of databases and functions.

● *External Sources (C_5)* enables working with big data by other tools.

● *Ease of Use (C_6)* points out how customers are satisfied with their usage experiences.

● *Support (C_7)* expresses the qualification of the support services provided by software developers in case of need.

The statistical summary of the retrieved dataset is presented in Table 3.

Table 3: Statistical summary of the dataset

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Mean	8.263	8.9875	8.0375	8.1375	8.0375	8.5375	8.4875
Median	8.400	8.9500	8.1500	8.4000	8.3000	8.4500	8.4500
Mode	8.400	8.7000	8.2000	8.5000	#N/A	8.4000	8.2000
Standard Deviation	0.532	0.2949	0.5975	0.8733	0.8434	0.2669	0.4549
Range	1.500	0.7000	1.8000	2.8000	2.2000	0.8000	1.5000
Minimum	7.300	8.7000	7.2000	6.3000	6.7000	8.3000	8.0000
Maximum	8.800	9.4000	9.0000	9.1000	8.9000	9.1000	9.5000
Sum	66.100	71.9000	64.3000	65.1000	64.3000	68.3000	67.9000

Table 3 illustrates the measured values of each alternative for every criterion. Notably, criterion C_2 registered the highest mean value (8.9875), whereas the lowest mean value was recorded for C_3 and C_5 (8.0375). Regarding standard deviation, criterion C_4 demonstrated the highest variability (0.8733), whereas criterion C_6 displayed the lowest variability (0.2669). Furthermore, the lowest measurement value was observed at C_4 (6.3) while the highest measurement value was recorded at C_7 (9.5). Similar conclusions can be drawn for other indicators.

All the criteria mentioned above are considered benefit-type criteria in the analysis. The first step of the analysis is determining the criteria weights. To obtain these criteria weights the PSI method was employed. The initial decision matrix was generated as in Table 4.

Table 4: Initial decision matrix of the problem

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
BDA_1	8.4	9.2	8.2	8.3	8.2	8.4	8.0
BDA_2	8.4	8.7	7.3	8	7.6	8.7	8.4
BDA_3	8.7	9.4	8.2	8.5	8.4	8.5	8.2
BDA_4	8.7	8.7	7.8	9.1	8.8	8.6	8.5
BDA_5	8.8	8.7	9	8.8	8.7	8.3	8.6
BDA_6	8.1	8.8	8.5	8.5	8.9	8.4	8.5
BDA_7	7.3	9.3	7.2	6.3	6.7	8.3	8.2
BDA_8	7.7	9.1	8.1	7.6	7	9.1	9.5

After the initial decision matrix was constructed, the normalization process was performed using Eq. (2). This process converts measurement units to the [0,1] interval. The normalized decision matrix (R) was obtained and is presented as in Table 5.

Table 5: The normalized decision matrix (R)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
BDA_1	0.9545	0.9787	0.9111	0.9121	0.9213	0.9231	0.8421
BDA_2	0.9545	0.9255	0.8111	0.8791	0.8539	0.9560	0.8842
BDA_3	0.9886	1.0000	0.9111	0.9341	0.9438	0.9341	0.8632
BDA_4	0.9886	0.9255	0.8667	1.0000	0.9888	0.9451	0.8947
BDA_5	1.0000	0.9255	1.0000	0.9670	0.9775	0.9121	0.9053
BDA_6	0.9205	0.9362	0.9444	0.9341	1.0000	0.9231	0.8947
BDA_7	0.8295	0.9894	0.8000	0.6923	0.7528	0.9121	0.8632
BDA_8	0.8750	0.9681	0.9000	0.8352	0.7865	1.0000	1.0000

The preference value PV_j for each criterion was calculated using Eq. (4)-(5) and the elements of *R*. Using these values, the deviation from preference value (Φ_j) was computed for each criterion using Eq. (6) and subsequently, the overall preference value (Ψ_j) was determined for each criterion using Eq. (7). All these values were presented in Table 6.

Table 6: Some values required to calculate the criteria weights

	PV	Φ_j	Ψ_j
C_1	0.0256	0.9744	0.1436
C_2	0.0069	0.9931	0.1463
C_3	0.0308	0.9692	0.1428
C_4	0.0645	0.9355	*0.1378*
C_5	0.0629	0.9371	0.1381
$\boldsymbol{C_6}$	0.0060	0.9940	**0.1464**
C_7	0.0160	0.9840	0.1450

In Table 6 the overall preference value (Ψ_j) serves as the weight of each criterion. Based on the values extracted from Table 5 it is discerned that *Ease of Use (C_6)* holds the utmost significance among the criteria. Conversely, *Data Workflow (C_4)* emerges as the least significant criterion among all the considered criteria. Despite the distinctions in weight values, it's noteworthy that the differences between the criteria weights are relatively subtle.

The PSI method, utilized for deriving criteria weights, inherently offers a dual output. While its primary purpose is to establish the weights in this paper, it concurrently generates an alternative ranking using Eq. (8), as demonstrated in Table 7. The rankings of the alternatives were pointed out in Table 7 according to the preference selection index values.

Table 7: The preference selection index values and rankings

Alternative	I	Rank
BDA_1	0.9205	5
BDA_2	0.8955	7
BDA_3	0.9393	3
BDA_4	0.9436	2
$\boldsymbol{BDA_5}$	**0.9548**	**1**
BDA_6	0.9357	4
BDA_7	0.8362	8
BDA_8	0.9109	6

Following the PSI methodology, the alternative with the highest preference selection index (PSI) is considered the most favorable choice. In adherence to this criterion, BDA_5 has emerged as the optimal selection, signifying superior performance compared to its counterparts. Conversely, BDA_7 has been identified as the least proficient alternative within this context.

The ARAS method was applied in the second phase for alternative ranking, leveraging criteria weights derived from the initial PSI stage. In preparing for the ARAS method, the extended initial decision matrix was formulated using Eq. (10), considering the absence of known optimal criterion values. Given the benefit-oriented nature of all criteria, Eq. (11) was not invoked. The resulting extended initial decision matrix is explicitly presented in Table 8 for clarity.

Table 8: The extended initial decision matrix for the ARAS method

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
BDA_0	8.8	9.4	9	9.1	8.9	9.1	9.5
BDA_1	8.4	9.2	8.2	8.3	8.2	8.4	8
BDA_2	8.4	8.7	7.3	8	7.6	8.7	8.4
BDA_3	8.7	9.4	8.2	8.5	8.4	8.5	8.2
BDA_4	8.7	8.7	7.8	9.1	8.8	8.6	8.5
BDA_5	8.8	8.7	9	8.8	8.7	8.3	8.6
BDA_6	8.1	8.8	8.5	8.5	8.9	8.4	8.5
BDA_7	7.3	9.3	7.2	6.3	6.7	8.3	8.2
BDA_8	7.7	9.1	8.1	7.6	7	9.1	9.5

In this table, each element of the first row represents the value of the optimal criterion. Employing Eq. (12) on the extended decision matrix facilitated the normalization process. This step transforms the measure units to a standardized [0,1] interval. For transparency and reference, the normalized decision matrix is depicted in Table 9.

Table 9: The normalized decision matrix for the ARAS method

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
BDA_0	0.1175	0.1156	0.1228	0.1226	0.1216	0.1176	0.1227
BDA_1	0.1121	0.1132	0.1119	0.1119	0.1120	0.1085	0.1034
BDA_2	0.1121	0.1070	0.0996	0.1078	0.1038	0.1124	0.1085
BDA_3	0.1162	0.1156	0.1119	0.1146	0.1148	0.1098	0.1059
BDA_4	0.1162	0.1070	0.1064	0.1226	0.1202	0.1111	0.1098
BDA_5	0.1175	0.1070	0.1228	0.1186	0.1189	0.1072	0.1111
BDA_6	0.1081	0.1082	0.1160	0.1146	0.1216	0.1085	0.1098
BDA_7	0.0975	0.1144	0.0982	0.0849	0.0915	0.1072	0.1059
BDA_8	0.1028	0.1119	0.1105	0.1024	0.0956	0.1176	0.1227

The normalized decision matrix underwent a weighting process using the criteria weights obtained via the PSI method and Eq. (14). The optimality function values (S_i) for each alternative were calculated based on the weighted decision matrix and Eq. (15). Subsequently, the utility degrees (K_i) were computed using the optimality function values and Eq. (16). The resulting rankings of the alternatives are presented comprehensively in Table 10 for a clearer overview.

Table 10: Results of the PSI-ARAS methodology

	S	K	Rank
BDA_0	0.1200	1.0000	
BDA_1	0.1104	0.9200	5
BDA_2	0.1074	0.8950	7
BDA_3	0.1127	0.9392	3
BDA_4	0.1132	0.9433	2
$\mathbf{BDA_5}$	**0.1146**	**0.9550**	**1**
BDA_6	0.1123	0.9358	4
BDA_7	0.1001	0.8342	8
BDA_8	0.1092	0.9100	6

According to the PSI-ARAS methodology, the top three performers are BDA_5, BDA_4, and BDA_3 showcasing the highest performances among their competitors. Conversely, BDA_8, BDA_2, and BDA_7 are identified as the least performers, exhibiting the lowest performances among their competitors. This ranking provides a comprehensive evaluation of the alternatives based on the given criteria weights and the ARAS methodology.

The analysis of findings from both the ARAS and PSI methods reveals a high degree of consistency. The fact that both methods yield fully consistent results under the given conditions underscores the reliability and coherence of the adopted approach. The consistency observed in the results indicates the robustness of the PSI-ARAS methodology employed in this study. This robustness suggests that the methodology can provide dependable outcomes in software selection for businesses undergoing digital transformation. BDA_5 emerges as the optimal software choice for serving business purposes in both methods. This convergence further reinforces the reliability of the selected software under the PSI-ARAS methodology. These insights affirm the efficacy and dependability of the proposed methodology for businesses seeking suitable BDA software in their digital transformation journey.

4.2. Comparative Analysis

The results of the proposed methodology were analyzed through a comparison with outputs from other prominent MCDM methods to validate and ensure the reliability of the PSI-ARAS methodology. Such comparative analyses make it possible to compare new MCDM methodologies proposed by researchers with the results of methods that already produce robust results and are known in the literature, allowing inferences about the reliability of newly proposed methods based on the compatibility of the obtained results. For analyses carried out for this purpose, Alkan and Kahraman (2024), Ul Haq et al. (2023), Tian et al. (2022), and Keshavarz-Ghorabaee et al. (2021) can be examined.

To achieve this, the same criteria weight set obtained with the PSI method was used as input for other MCDM methods. The methods included in the comparative analysis were MAIRCA (Pamučar et al., 2014), MABAC (Pamučar and Ćirović, 2015), CoCoSo (Yazdani et al., 2019), and MARCOS (Stević et al., 2020). These methods were selected for comparative analysis as they represent relatively new approaches in the MCDM literature and have gained significant traction among MCDM practitioners. The obtained rankings are depicted in Figure 2.

According to the outcomes in Figure 2, BDA_5 emerged as the top BDA software alternative for PSI, PSI-ARAS, and MARCOS methods, while MAIRCA and MABAC methods ranked it as the second-best alternative. In contrast, BDA_3 claimed the top spot for MAIRCA, MABAC, and CoCoSo methods. Notably, BDA_2 and BDA_7 consistently ranked as the least favorable alternatives across all methods. In summary, PSI and MARCOS methods produced identical solutions to the proposed method, while MAIRCA and MABAC yielded similar results. However, CoCoSo exhibited slight differences from the proposed method. According to the results of the comparative analysis, the proposed PSI-ARAS method aligns well with current methods in the MCDM literature. This confirmation suggests that the proposed method can yield valid and reliable results. The Spearman correlation coefficients, calculated based on the results presented in Figure 2, are provided in Table 11.

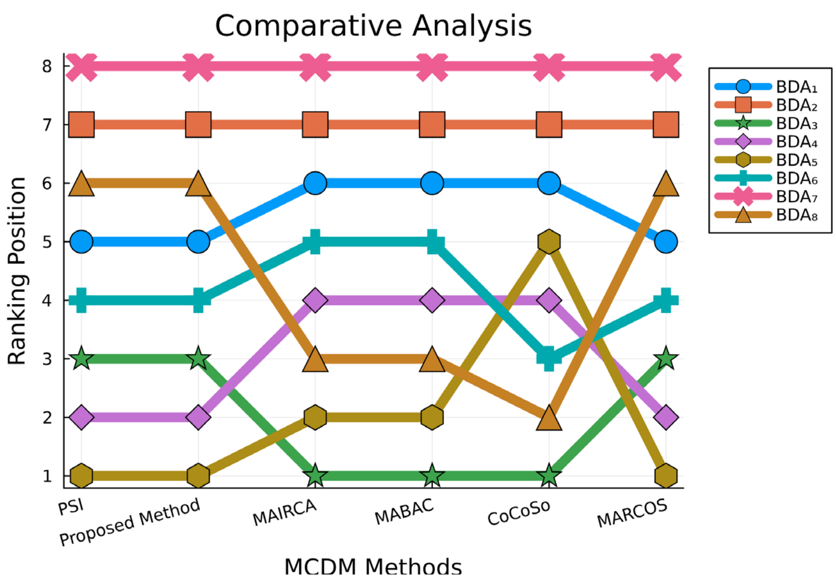

Figure 2: Visualization of the comparative analysis

Table 11: Spearman Correlation Coefficient of Methods

	PSI	PSI-ARAS	MAIRCA	MABAC	CoCoSo	MARCOS
PSI-ARAS	1.00	1.00	0.76	0.76	0.50	1.00
PSI		1.00	0.76	0.76	0.50	1.00
MAIRCA			1.00	1.00	0.83	0.76
MABAC				1.00	0.83	0.76
CoCoSo					1.00	0.50
MARCOS						1.00

Based upon the interpretation of correlation coefficients by Schober et al. (2018: 1765) the proposed method exhibits a very strong correlation $(\rho = 1)$ with the PSI and MARCOS methods, and a strong correlation $(\rho = 0.76)$ with the MAIRCA and MABAC methods. These findings statistically support the visual inferences made based on Figure 2.

5. CONCLUSION

This paper addresses a challenging problem in Big Data Analytics (BDA) software selection from a Multi-Criteria Decision Making (MCDM) perspective, particularly for businesses transitioning into digital enterprises. To achieve this goal, a two-stage methodology is designed to investigate the BDA software selection problem. The methodology combines the PSI and ARAS methods. The first stage of the methodology is focused on determining criteria weights. The analysis of the values derived from the PSI method indicates that Ease of Use (C_6) is the most significant criterion as in Hanine et al., (2016), Tuş and Aytaç Adalı (2019), while Data Workflow (C_4) is the least significant among all the criteria examined. Although there are variations in the weight values, it is important to note that the differences between the criteria weights are relatively minor. Despite the type of software selected varied, the most important criterion was found to be in line with existing studies in the literature. The second stage ensures ranking alternatives. Among their competitors, the top three performers identified by the PSI-ARAS methodology are BDA_5, BDA_4, and BDA_3 showcasing the highest performance. Conversely, BDA_8, BDA_2, and BDA_7 are identified as the lowest performers, exhibiting the lowest performance. The PSI-ARAS methodology fills a significant gap in the BDA software selection literature, offering a valuable tool for practitioners or organizations with similar needs.

During the analysis phase, 8 widely used BDA software options were examined in the market based on 7 criteria. After applying the PSI method, the analysis revealed that Ease of Use was the most crucial criterion, while Data Workflow ranked as the least important criterion. Subsequently, the alternatives were ranked using the ARAS method based on the obtained criteria weights. These ranking results were further compared with the alternative ranking derived from the PSI method. Upon comparing the results, it was evident that they were entirely consistent. This study identified the software alternative labeled BDA_5 as the optimal choice in both scenarios. To validate the proposed solution method, comparative analyses were conducted with MAIRCA, CoCoSo, MABAC, and MARCOS methods, alongside PSI. The results indicated a very strong correlation between the PSI-ARAS method and the PSI and MARCOS methods while showing a strong correlation with MAIRCA and MABAC methods.

5.1. Managerial Implications

These findings hold significant managerial implications in two dimensions. For traditional businesses transitioning into digital businesses realms through digital transformation, employing MCDM methods provides a strategic avenue to discern software or technological processes related to big data. This enables aligning choices with organizational objectives and investment policies. Conversely, software developers can leverage similar approaches to align with user preferences. By identifying what users deem crucial for their existing or prospective products, developers can not only position their offerings favorably against competitors but also elevate the satisfaction levels of their existing customer base.

5.2. Limitations and Further Studies

As with any study, there are several limitations in this research. Firstly, the study focuses on general-purpose Big Data Analytics (BDA) software, which serves a wide range of fields, thereby utilizing available datasets for analysis. However, if a more specific dataset based on user experiences or expert evaluations were available, it could provide insights into potential differences in criterion weights and rankings obtained in this study. Additionally, limitations exist in exploring variations based on user type, purpose of software use, or user expertise level.

In future research, more specific studies focusing on particular purposes such as data storage, visualization, integration, etc., can be conducted to cater to the diverse needs of different sectors. Moreover, there is an opportunity to expand the scope of research by integrating subjective evaluations that incorporate uncertainties derived from decision-makers' experiences, thus enabling analyses with various Multi-Criteria Decision Making (MCDM) methods. Decision-making under uncertain environments could benefit from MCDM methods based on fuzzy, intuitionistic fuzzy, hesitant fuzzy, plithogenic, or neutrosophic numbers. While this study selected Big Data Analytics (BDA) software with a general approach, future studies can tailor the selection process to meet sector-specific needs, including banking, healthcare, insurance, manufacturing, logistics, etc.

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